Sectoral Effects of News Shocks

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Abstract

This paper argues that an aggregate news shock reveals news about technological improvements in the durable goods sector. Better technological prospects translate into large responses of the fundamentals in the durable goods sector; much larger than the responses of the fundamentals in the nondurable goods sector. These better technological prospects, contrary to common belief, do not induce short-run comovement among fundamentals within either of the two sectors. The behavior of inventories, an important margin that durable goods producers can use to buffer news shocks, proves to be crucial for reconciling the effects of news shocks in a two-sector model with the data.

Keywords: News Shock, Durable and Nondurable Goods Sectors, Inventories

JEL Classification Codes: E3, E32, L60

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1 Introduction

After being abandoned for more than half a century, the idea that the expectations about future changes in productivity represent an important driving force of the business cycle has experienced a revival, receiving a great deal of attention in the recent literature.[1] Beaudry and Portier (2004, 2006) were the first authors to reassess the importance of news about future technological developments as drivers of business cycles. They find that news shocks account for more than half of output (business-cycle) fluctuations and also induce comovement among aggregate variables.[2]

The purpose of this paper is to gain deeper understanding about the nature of this important shock, by looking at the channels through which it propagates the business cycle. Specifically, I analyze the behavior of the manufacturing sector, because it allows for a clear distinction between the nondurable and durable goods industries. As I will show, the aggregate news shock is essentially a durable-goods-sector news shock, which implies that durable goods industries play a dominant role in the propagation of an aggregate news shock. This result is consistent with Mankiw (1985), who concludes that durable goods industries play an essential role in the business cycle, and that explaining fluctuations in the durable goods sector is vital for understanding aggregate economic fluctuations.

This paper argues that an aggregate news shock is effectively a news shock about technological improvements in the durable goods sector. Better technological prospects translate into large responses of the fundamentals in the durable goods sector; much larger than the responses of the fundamentals in the nondurable goods sector.[3] These better technological prospects, however, do not induce short-run comovement among fundamentals within either of the two sectors. This lack of the short-run comovement can be better understood by looking at the behavior of inventories, an important margin that durable goods producers can use to buffer news shocks. In fact, my investigation of inventories within a two-sector model proves to be crucial for understanding the propagation channel of an aggregate news shock to the two sectors, and to reconciling the short-run effects of news shocks in a model with the data.

My empirical analysis relies on the identification proposed by Barsky and Sims (2011), in which an aggregate news shock is identified as the shock that has no contemporaneous impact on total factor productivity (TFP) and that simultaneously explains most of its forecast error variance over the 10-year horizon.[4] The contribution of this empirical analysis consists of two parts. First, my

[1] Pigou (1927) was one of the first authors to propose that agents' expectations about the future are an important source of business-cycle fluctuations.

[2] Jaimovich and Rebelo (2009), Beaudry and Lucke (2010) and Schmitt-Grohé and Uribe (2012) also find news shocks to be an important driver of business-cycle fluctuations. For a very detailed survey of the papers that contribute to this literature see Beaudry and Portier (2014).

[3] Throughout this paper, I consider fundamentals to be the following variables of interest: productivity, stock prices, output, consumption, investment, and hours worked. The term "sectoral fundamentals" refers to these variables in the durable goods or nondurable goods sectors.

[4] My results are robust to the use of different time horizons and a slightly different identification, proposed by

sector-focused investigation shows that an aggregate news shock manifests as a durable-goods-sector news shock, and, therefore, propagates primarily through the durable goods sector. In particular, after a one percent aggregate news shock, the response of durable-goods-sector productivity after a three-year horizon is already about three times greater than the response of the nondurable-goods-sector productivity. This higher productivity increase translates into significantly higher percentage responses of fundamentals in the durable goods sector than in the nondurable goods sector. Second, my sector-focused investigation also shows that a positive aggregate news shock does not generate comovement among sectoral fundamentals within the two sectors. In particular, a positive aggregate news shock leads to the following responses: positive investment in both sectors; negative hours and output in both sectors. In addition, aggregate news shocks introduce negative correlation in consumption across sectors, different from the positive unconditional correlation observed in the data.[5]

It has been long understood that the producers of durables can stock inventories and use them to buffer shocks. Nearly a century ago, Pigou (1927) proposed that the possibility of holding stocks of inventories explained the fact that business-cycle fluctuations are more pronounced in durable, rather than nondurable, goods industries. Early research in the real business-cycle tradition (see Blinder (1986), Christiano and Eichenbaum (1987), Eichenbaum (1984), Ramey (1989)) focused considerable attention on the importance of explaining the behavior of inventories.[6] In my analysis, I re-establish the role of the importance of inventories with new empirical evidence concerning the response of inventories to news shocks, connecting the two literatures. To do so, I use the inventories-to-sales ratio, a standard inventories indicator. The resulting percentage response of inventories to news is statistically significant in the durable goods sector, reinforcing the notion of the importance of inventories specifically in the durable manufacturing subsector (e.g. Blinder and Holtz-Eakin (1984), Feldstein and Auerbach (1976)).

This large and significant response of inventories in the durable goods sector to a news shock suggests that the behavior of inventories might carry relevant information for understanding the propagation of news shocks and business cycles.[7] Therefore, to explore the mechanism, I build a

Francis, Owyang, Roush, and DiCecio (2014), and used by Beaudry et al. (2011) for the purposes of identifying news shocks. My results are also in line with Theodoridis and Zanetti (2016) who show that their findings are robust across different identification strategies as well as across horizons of 40, 80 and 120 quarters.

[5] Long and Plosser (1983) were the first to point out that the comovement of different sectors represents an important feature of business cycles. In addition, Christiano and Fitzgerald (1998) document a strong comovement between hours worked in different sectors of the economy, while Rebelo (2005) documents that this comovement persists also when a more disaggregated classification of industries is considered. My paper relates to this literature as it investigates comovement within and between the two specific sectors of the economy. However, the focus of this paper is on understanding the effects and relevance of a specific shock, i.e. news shock, by studying the comovement that it induces.

[6] More recently, many papers have looked at the aggregate implications of introducing inventories into dynamic general equilibrium models (e.g. Fisher and Hornstein (2000), Bils and Kahn (2000), Kahn (2008a,b), Kryvtsov and Midrigan (2013)).

[7] To the best of my knowledge, Crouzet and Oh (2016) is the only paper that investigates inventories dynamics in the context of the news literature; these authors document that the dynamics of the inventories-to-sales ratio is crucial

model with an explicit role for inventories in the durable goods sector. Specifically, my model is a two-sector, two-factor, real business cycle model that follows Baxter (1996) in its basic structure. Sector 1 produces a pure consumption (nondurable) good, whereas sector 2 produces a consumer durable good and the capital good that is used as an input in the production of both consumption goods. Both sectors use capital and labor as their factor inputs. The key difference between the two sectors is that a good produced in sector 1 is perishable, whereas a good produced in sector 2 can be stocked. I model this feature by adding inventories into the production function of sector 2, following Christiano (1988) and Kydland and Prescott (1982). These authors argue that the stock of inventories, as the stock of fixed capital, provides a flow of services to a firm.

My model features several additional components. First, it requires adjustment costs both in investment and in new purchases of durable goods, because this gives the agents an incentive to respond to positive news immediately. Second, variable capital utilization in both sectors serves an important function by creating a channel through which hours and output can respond to news shocks. Third, my model introduces preferences with a weak short-run wealth effect on the labor supply. This feature plays an important role in securing my results because the empirical evidence does not easily square with a two-sector real business cycle model with standard preferences of the King et al. (1988) type. While these preferences are desirable for obtaining a negative response of labor supply at the aggregate level, they cannot generate comovement between hours worked across the two sectors. Therefore, a model with the capacity to reproduce empirical evidence must feature preferences with a weak short-run wealth effect on the labor supply. Finally, as mentioned above, durable goods sector requires inventories for production.

These components together explain the observed empirical responses. Specifically, the model can replicate the negative impact responses of hours in both sectors. The presence of inventories proves to be crucial for this result. In fact, contrary to the situation when inventories are not present in the model, utilization rates in both sectors - especially in the durable goods sector - decrease on impact, leading, in turn, to a decrease in hours and outputs in both sectors. Lower labor supply, together with lower utilization rates, leads to a decline in output in both sectors. As output in the nondurable goods sector decreases, so does the nondurables' consumption. However, since the durable goods sector can hold inventories, as output decreases in this sector, both consumption and investment can increase at the same time as the stock of inventories adjusts to meet higher demand for new purchases of durable consumption goods as well as for investment goods used in the production of the two sectors. In addition, the model performs remarkably well in replicating my first empirical result, i.e. larger responses of the durable-goods-sector fundamentals to an aggregate news shock over longer horizons.

for the identification of aggregate news shocks. However, they do not investigate sectoral components of aggregate news shock and the role of inventories in explaining these components.

Although this is the first paper to distinguish between the durable and nondurable goods sectors of the economy, several papers in the recent literature focus on disentangling sectoral components of aggregate news shocks. For example, Ben Zeev and Khan (2015) show that investment-specific news shocks constitute a significant force behind U.S. business cycles and account for about 70 percent of business-cycle variations in output. Görtz and Tsoukalas (2017), by looking at sectoral data and documenting high co-linearity between consumption-specific and investment-specific news shocks, document the importance of both aggregate and investment-specific news shocks in explaining aggregate U.S. fluctuations. Furthermore, by looking at the financial sector of the economy, Görtz, Tsoukalas, and Zanetti (2016) show that the movements in credit spreads are crucial for the propagation of news shocks. Finally, Nam and Wang (2014) show that investigating sectoral components of aggregate news shocks matters for the implications of news shocks.[8]

The remainder of the paper is structured as follows: Section 2 discusses the choice of the benchmark identification strategy, as well as the data used in the empirical analysis. Section 3 presents the main empirical findings, by analyzing the responses of sectoral fundamentals to aggregate news. The two-sector model is presented in Section 4, and its calibration in Section 5. Quantitative findings of the model and their robustness are presented in Section 6. Section 7 concludes.

2 Empirical Strategy

When the effects of a particular exogenous shock are discussed in macroeconomics, an important first step is to clearly communicate the validity of the identification strategy used. There are several identification strategies proposed in the news literature. In this paper I adopt the strategy proposed by Barsky and Sims (2011) (BS identification, henceforth) as the benchmark strategy, with technical details provided in Appendix A. I then perform several robustness checks, and report them in Appendix B. Specifically, I investigate robustness of the results across different forecast horizons with the benchmark strategy, as well as across different identification strategies, the one proposed by Francis, Owyang, Roush, and DiCecio (2014) and the one proposed by Beaudry and Portier (2006).

[8]Many authors have studied the importance and propagation of aggregate news shocks in a context of a structural model. For example, Schmitt-Grohé and Uribe (2012) estimate a dynamic stochastic general equilibrium (DSGE) model augmented with several real rigidities, and find that news shocks account for more than two thirds of predicted aggregate fluctuations in output, consumption, and investment growth. Theodoridis and Zanetti (2016) estimate real business cycle (RBC) model augmented with search and matching frictions on the labor market as well as some real frictions, using Bayesian techniques, and show that a model with news shocks provides remarkable fit of the data, suggesting the importance of the inclusion of these shocks. By using a structural DSGE model augmented with financial frictions, Görtz, Tsoukalas, and Zanetti (2016) show that technological news shocks account for about one third of output fluctuations and up to 42 percent of variations in hours worked. It is worth noting that these results are sensitive to the inclusion of nominal price and wage rigidities as shown by Khan and Tsoukalas (2012). In particular, these authors show that the presence of nominal rigidities reduces importance of news shocks to accounting for less than 15 percent of the variance in output growth, with non-technological sources of news dominating technological news.

2.1 Identification of News Shocks

Regardless of the identification strategy used, a news shock is typically defined as the arrival of new information about future productivity growth that is instantaneously reflected in forward-looking variables, but has no instantaneous impact on current productivity. Instead, the effects on TFP are realized only after a certain number of quarters. Although it is relatively straightforward to think about this phenomenon in a theoretical framework, recovering its empirical analog is more challenging.

My choice of the benchmark identification strategy is guided by the fact that it overcomes the recent criticisms of the Beaudry and Portier's identification, the first identification strategy of technological news shocks to be proposed in the literature.[9] Specifically, Barsky and Sims apply the strategy proposed by Uhlig (2004) for the purpose of identifying a news shock. They identify the news shock as the shock that has no contemporaneous impact on TFP and that explains most of its forecast error variance over the 10-year horizon.[10] The advantage of this approach is that it circumvents the problem pointed out by Kurmann and Mertens (2014) because it does not rely on long-run restrictions. In addition, it can be applied to larger-scale VAR systems without imposing any additional restrictions. Therefore, I use large-scale VAR systems that will be described below. To improve precision, following Kurmann and Otrok (2013), I impose a Minnesota prior (see Hamilton (1994), pages 360-362) on the estimation, and I compute error bands by drawing from the posterior.[11]

2.2 Data

The data used in this paper can be divided into two categories: aggregate-level and sector-level data. They both span the period 1972:Q1-2012:Q4. At the sectoral level, I use data from the

[9]For example, Fisher (2010) points out that when a vector error correction model is used, as it is the case with the BP identification, the conclusions regarding the importance of news shocks greatly depend on the number of cointegration relationships imposed. Similarly, Kurmann and Mertens (2014) show that the problem of Beaudry and Portier's identification scheme arises in a system with more than two variables as a result of combining long-run restrictions and cointegration restrictions. In particular, as it turns out, one of the long-run restrictions becomes redundant, making it impossible to uniquely identify the solution. At the same time, Forni, Gambetti, and Sala (2014) point out that small-scale vector autoregression (VAR) models, such as the one used by Beaudry and Portier, suffer from the nonfundamentalness issue, as the variables used do not contain enough information to recover structural shocks.

[10]This horizon is used in all specifications where news shock is identified using the benchmark specification.

[11]In particular, H, the prior variance for the VAR coefficients, is a diagonal matrix with $(i,j)^{th}$ element, corresponding to lag l, as follows:

$$H_{ij,l} = \begin{cases} (\frac{\lambda_1}{l^{\lambda_3}})^2 & \text{if } i = j \\ (\frac{\sigma_i \lambda_1 \lambda_2}{\sigma_j l^{\lambda_3}})^2 & \text{if } i \neq j \\ (\sigma_i \lambda_4)^2 & \text{for intercepts,} \end{cases}$$

where i refers to the dependent variable and j to the independent variables in the i^{th} equation. Term σ_i is a standard deviation of error terms from an OLS regression of i^{th} variable on a constant and l of its own lagged values. The values for hyperparameters are chosen as follows: $\lambda_1 = 0.2$, $\lambda_2 = 0.5$, $\lambda_3 = 1$, and $\lambda_4 = 10^5$.

manufacturing sector, which allows me to clearly distinguish between durable and nondurable goods industries.[12]

At the aggregate level, I use the technology measure constructed and detailed by Fernald (2012).[13] Since Fernald calculates only aggregate technology measures, I construct my own corrected empirical measures of sector-specific technology measures. In order to do so, I start by following the approach proposed by Burnside et al. (1995), and assume that time t gross output is produced using a Leontief production function given by

$$Y_t = \min\left(M_t, V_t\right), \tag{1}$$

where M_t denotes time t materials and V_t denotes value-added at time t, which, itself, is produced using primary inputs, namely total hours worked L_t, the stock of capital K_t, and time-varying capital utilization, u_t. Because material inputs enter the production function with exponent of one, that is, because the production function is homothetic, this specification leads to gross output that is equal to value added and is only a function of primary inputs. For this reason, the chosen specification allows me to work with sectoral gross output data despite the lack of data on material inputs. Then, the only remaining step towards constructing TFP measure is to define how primary inputs are combined in the production of value added. Following the steps outlined in Burnside et al. (1995), total value added in sector i may be written as

$$V_t^i = A_t^i F\left(N_t^i H_t^i, K_t^i H_t^i\right). \tag{2}$$

Here A_t^i reflects the state of time t technology and other exogenous factors that affect productivity in sector i, N_t^i is the number of sector i's time t workers and H_t^i is the number of hours they are employed which, in this specification, coincides with the workweek of capital. Total hours worked in sector i, L_t^i, is the product of these two variables.

Following Burnside et al. (1995) who argue that the sector-level and industry-level data are well described by a constant-returns-to-scale production function, I assume that the function $F(\cdot)$ takes the Cobb-Douglas form. Then, using equations (1) and (2), i.e. the fact that gross output is equal to value added that is in turn function of primary inputs, the expression for technology in sector or

[12] I do not consider services sector due to data limitations. In particular, all data that are provided by the Federal Reserve Board, and used for the construction of TFP and output measures are not available for the services sector. In addition, there is large evidence of the existence of constant returns to scale in manufacturing industries, which is crucial for the construction of TFP measure, as discussed by Basu and Fernald (1994), Burnside et al. (1995) and Burnside (1996), among others.

[13] As emphasized by Beaudry and Portier (2006) and Barsky and Sims (2011), since the identification of news shocks requires orthogonalization with respect to observed technology, it is important that the empirical measure of technology controls for the unobserved input variations. The advantage of Fernald's approach is that it uses a careful growth accounting, which controls for heterogeneity among workers and types of capital and adjusts for variation in factor utilization - labor effort and the workweek of capital.

industry i can be obtained using a first-order log-linear approximation of the production function:

$$\Delta Y_t^i = \alpha_i \Delta L_t^i + (1-\alpha_i)\,\Delta K_t^i u_t^i + \Delta A_t^i, \tag{3}$$

where ΔA_t^i is assumed to be the growth rate of TFP, ΔY_t^i the growth rate of output, ΔL_t^i the growth rate of labor input, α_i is the labor share in income and $\Delta K_t^i u_t^i$ the growth rate of capital services adjusted for the capacity utilization in sector i, u_t^i.

In addition to Fernald's aggregate TFP measure, other aggregate-level variables used are: consumption (Real Personal Consumption Expenditures on Nondurable Goods and Services, from the U.S. Bureau of Economic Analysis (BEA) National Income and Product Accounts (NIPA) tables), output (Seasonally Adjusted Total Non Farm Output from the U.S. Bureau of Labor Statistics (BLS), series PRS85006033)), hours (Seasonally Adjusted Total Non Farm Hours from the BLS, series PRS85006033)), stock prices (Standard and Poor's 500 Composite Stock Price Index), consumer confidence (from the Michigan Survey of Consumers as in Barsky and Sims (2011)).

The sector-specific gross output measure is the industrial production index. The capital measure is the log of real capital services corrected for capacity utilization. Industrial production and capacity utilization measures are from the Federal Reserve Board (Industrial Production and Capacity Utilization - G.17), while the capital services series are obtained from the BEA NIPA tables (Chain-Type Quantity Indexes for Net Stock of Private Fixed Assets by Industry, Table 3.2ESI), and interpolated to obtain quarterly series, as in Beaudry and Portier (2006).[14]

The labor measure is the hours worked by the production workers, which is constructed as the product of the following two time series in each sector: average weekly hours of production workers and the total number of production workers, both obtained from the BLS.[15] Finally, my assumption of a constant-returns-to-scale Cobb-Douglas technology allows me to calibrate the parameter α_i, using the labor share in income. I compute labor's share as the ratio of labor compensation (BEA's Compensation of Employees by Industry) and nominal income (BEA's Value Added by Industry) in each sector.[16]

The sector-specific consumption measure is the log of the real durable and non-durable goods consumption (BEA's Gross Domestic Product and Personal Income), and the investment measure is

[14] Ideally, to avoid interpolating the series, one would follow the approach proposed by Burnside et al. (1995), who assume that electricity consumption per machine is proportional to its workweek, which then allows them to use quarterly series on electricity consumption as a proxy for capital services. In particular, they show that the production in sector i is: $Y_t^i = A_t^i F\left(L_t^i, E_t^i/\phi\right)$, where ϕ represents the assumed fixed proportion between electricity consumption and capital services. Federal Reserve, however, discontinued its survey of industrial electric power in 2006, because the response rate for the voluntary survey had dropped significantly. As a robustness check I confirm that, for the part of the sample in which electricity consumption is available, my sector-level results are robust to the use of these two different measures of capital services in constructing technology measures. Therefore, I am confident that my results are not influenced by the data used to measure capital services.

[15] Employment, Hours, and Earnings from the Current Employment Statistics survey (National), with the series: CES3100000006, CES3100000007, CES3200000006 and CES3200000007.

[16] Because the data is available at annual frequencies I assume constant labor share over one year.

the Index for Investment in Private Fixed Assets by Industry (BEA's Fixed Assets). As an inventories indicator I construct the log of the real inventories-to-sales ratio, using the data on change in real private inventories and real final sales by industry (BEA's Gross Domestic Product and Personal Income).

The measure of industry stock prices is the log of the real stock price index, taken from Kenneth French's website.[17] Using the civilian non-institutional population over 16 (BLS series LNU00000000Q), I convert all the data to per capita measures.

3 Empirical Evidence

What is the nature of an aggregate news shock? Does it affect all sectors of the economy equally, or does it propagate only through a specific sector? In order to answer the first question, I explore the effects of an aggregate news shock on sectoral productivities and stock prices. In order to answer the second question and better understand the transmission mechanism of this shock, I explore the effects on the durable goods and nondurable goods sectors, by analyzing sector-specific responses of output, consumption, investment, hours, and inventories.

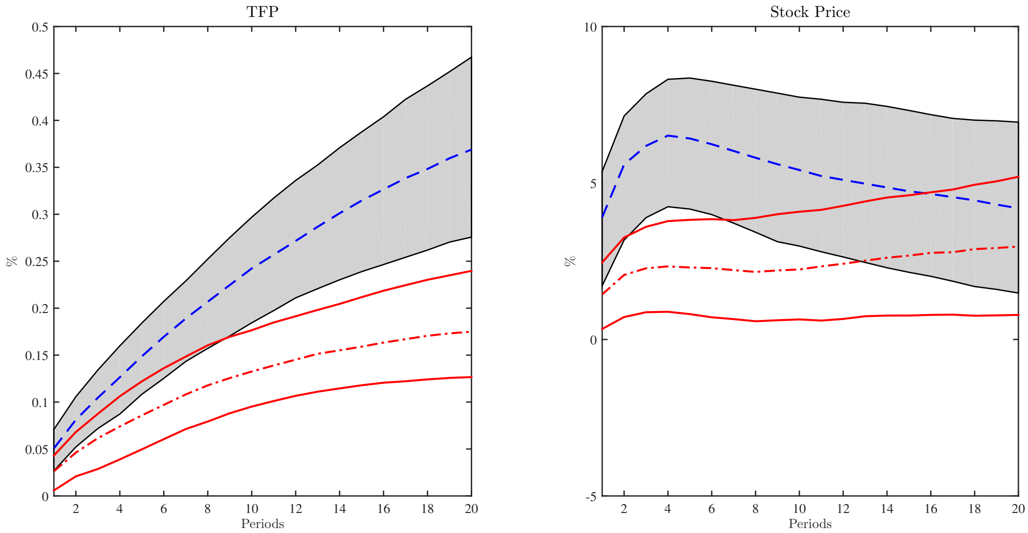
3.1 Technology and Stock Prices

An aggregate news shock might not affect sector-specific productivities and stock prices in the same manner. In fact, I show that aggregate forward-looking variables contain different information about the productivities in the two sectors, and, therefore, have different implications across durable and nondurable goods industries. The responses of sectoral productivities and stock prices to an aggregate news shock are reported in Figure 1.

The quantitative responses of the two sectors are remarkably different. First, the impact response of the durable goods sector stock price index is about three times larger than that of the nondurable goods sector, with nondurable response lying outside the durable goods sector confidence bands. In addition, besides the first quarter, confidence bands in the two sectors do not overlap and only start to converge over longer horizons, after the initial information is disseminated. Several authors have emphasized forward-looking variables' predictive power regarding future movements in economic activity. Therefore, more responsive durable goods sector stock prices over shorter horizons suggest that an aggregate news shock mostly reflects the sector's higher future productivity, and, thus, real activity as well. In fact, this view is confirmed in the next section when I look at other sectoral fundamentals. Second, after similar nearly-zero initial responses, productivities in the two sectors

[17] The data are constructed using The Centre for Research in Security Prices (CRSP) database. The particular series used here are the stock price indices of the manufacturing's durable goods and nondurable goods sector, using the average value weighted returns. The data are available for download at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html under *Industry Portfolios*.

Figure 1: Impulse responses of the sectoral TFPs and Stock Price Indices to a unit aggregate news shock



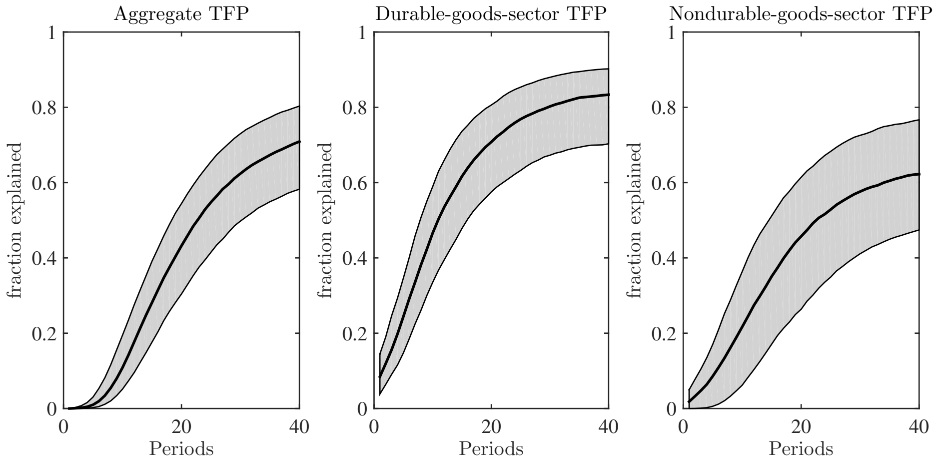
Note: The dashed (durable goods sector) and dash-dotted (nondurable goods sector) lines are the estimated impulse responses to a unit aggregate news shock (BS identification), and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The responses originate from a VAR featuring eight variables: six aggregate variables, namely TFP, consumption, output, hours, stock price index, and consumer confidence, and two sectoral variables, TFP and stock price index in the durable goods sector and in the nondurable goods sector, alternatively. The system is estimated in the levels of all variables, features four lags and a constant. The gray areas and the solid lines represent +/- one standard deviation confidence bands, obtained by drawing from the posterior, in the durable and the nondurable goods sector, respectively.

quickly start to diverge. Specifically, the percentage response of the TFP in the durable goods sector rapidly eclipses that of the TFP in the nondurable goods sector; after just a three-year horizon it is about two times greater. At the same time, while confidence bands overlap over the shorter horizons while the new technology is not yet adopted, they quickly start to diverge over the longer horizons when TFP in the durable goods sector increases significantly more than in the nondurable goods sector.

In order to investigate how important a news shock is in driving these responses, Figure 2 plots the forecast error variance of the aggregate news shock in explaining TFP, both in the aggregate and for the two separate sectors. The results are striking: over a five-year horizon, an aggregate news shock explains more of the TFP movements in the durable goods sector than in the aggregate. Specifically, an aggregate news shock explains the total variance of TFP to the following extents: more than 80 percent for the durable goods sector, 60 percent for the nondurable goods sector, and about 70 percent in the aggregate. These results suggest that the overall lower productivity response in the nondurable goods sector is not because the news shock lacks importance, but because the aggregate news propagates mainly to the productivity in the durable goods sector, essentially representing news about technological improvements in this particular sector of the economy.

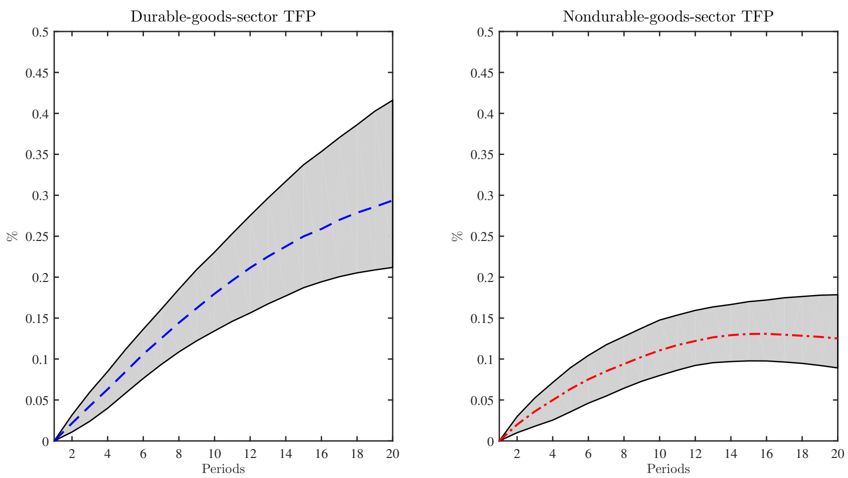
One might be concerned that the identification of the aggregate news shock will be affected once

Figure 2: Forecast Error Variance explained by aggregate news shock



Note: The solid lines are the estimated forecast error variance of TFP (aggregate, and for the durable goods and nondurable goods sectors) caused by an aggregate news shock, obtained using the benchmark identification and the specification as in Figure 1. The solid lines correspond to the posterior median estimates, while the gray areas represent +/- one standard deviation confidence bands obtained by drawing from the posterior.

Figure 3: Impulse responses of the sectoral TFPs to a unit sector-specific news shock



Note: The figure represents the responses of the sectoral TFPs to a unit news shock in a VAR composed of the durable goods sector TFP, aggregate consumption, output, hours, stock price index, and consumer confidence (left panel) and the nondurable goods sector TFP, aggregate consumption, output, hours, stock price index, and consumer confidence (right panel). Both systems are estimated in the levels of all variables, feature four lags and a constant. The news shock is identified using the BS identification, i.e. as the shock orthogonal to the sectoral (durable goods sector and nondurable good sector, alternatively) TFP innovations which best accounts for unexplained movements in sectoral TFP over a ten-year horizon. The dashed blue lines (left panel) and dash-dotted red lines (right panel) correspond to the posterior median estimates, while the gray areas depict +/- one standard deviation confidence bands obtained by drawing from the posterior.

the sectoral TFP is added to the system composed of aggregate variables. At least four points address this issue. First, the responses of the aggregate variables in the system barely change when sectoral variables are added. Second, the initial responses of productivities in both sectors are very close to zero (left panel of Figure 1), even though they are not restricted, suggesting that the identified shock does in fact represent a news shock about future productivity prospects. Third, Figure 3 displays the responses of sectoral TFPs when aggregate TFP is excluded from the system and when the contemporaneous sectoral TFP (first in the durable and then in the nondurable goods sector) is restricted to be zero instead. This specification identifies sector-specific components contained in the aggregate forward-looking variables (stock prices and consumer confidence). Interestingly, besides the very initial responses which are zero by construction in this specification, the responses of the sectoral TFPs are almost identical to those in the left panel of Figure 1. This result suggests that the two specifications essentially extract the same sector-specific information contained in the aggregate variables. Fourth, responses of sectoral TFPs are almost identical when a two-step procedure is used; in the first stage, an aggregate news shock is extracted from the aggregate system and then, in the second stage, sectoral productivities are regressed on the lags of aggregate news recovered in the first stage.[18]

In what follows, I explore broader implications of these results by analyzing whether aggregate news shocks also set off different impacts on sectoral fundamentals across the two sectors.

3.2 Other Sectoral Fundamentals

Although my first result shows that an aggregate news shock manifests as a durable-goods-sector news, other fundamentals might still behave quite similarly across the two sectors - depending on the propagation mechanism of the shock, and interactions between the sectors. To this end, I examine how the news literature's commonly considered variables - sectoral output, consumption, hours, and investment - respond to the aggregate news shock. One obvious and key difference between durable and nondurable goods is that producers of durables can stock inventories and use them to buffer shocks. Therefore, I also look at the behavior of inventories, which might paint a clearer picture regarding the responses of the two sectors.

Figure 4 displays the responses of sectoral fundamentals to a unit aggregate news shock. The responses originate from a seven-variable VAR featuring aggregate TFP, consumption, output, hours, stock price index, consumer confidence, and a sectoral variable which is alternatively output, consumption, investment, and hours in each sector. All VAR systems are estimated in the levels of all variables, feature four lags and a constant.[19] Two interesting outcomes emerge:

First, higher productivity in the durable goods sector translates into higher percentage responses of the fundamentals in the durable goods sector than in the nondurable goods sector. Specifically, besides the behavior of hours, which is not statistically different between the sectors, the responses

[18] Although the fact that the two procedures lead to very similar results is reassuring, I choose an augmented VAR in which sectoral fundamentals are added to the VAR composed of aggregate variables as the benchmark specification. This is because interactions between the aggregate and sectoral fundamentals could carry information relevant for characterizing responses of sectoral fundamentals to aggregate news.

[19] Estimating VARs in levels is consistent with the approach taken by the empirical VAR literature. For example, Barsky and Sims (2011) estimate the VAR in levels, following a conservative approach suggested by Hamilton (1994), which produces consistent estimates of the IRFs.

in the nondurable goods sector all lie outside the durable goods sector confidence bands. In addition, the confidence bands of consumption responses in the two sectors do not overlap; the confidence bands of output responses are not different across the two sectors over the shorter horizons, but start to diverge over the longer horizons as new technologies get adopted; the confidence bands of investment responses are mostly tangent across the two sectors. Overall, these results suggest that the aggregate news mainly propagates through the durable goods sector of the economy. Nevertheless, to investigate this fact further, I examine the fraction of the forecast error variance of the main aggregate and sectoral variables explained by an aggregate news shock. For the durable goods sector, an aggregate news shock accounts for levels of variance of output reaching more than one quarter after only two years, and more than one half after five years. Moreover, after 10 years the shock accounts for a larger share of the output variance in the durable goods sector than in aggregate output. By contrast, for the nondurable goods sector, aggregate news shock accounts only for a small fraction of the variance of output. These results suggest that aggregate news shocks represent a very important driving force behind economic fluctuations in the durable goods sector, and a less important driving force behind economic fluctuations in the nondurable goods sector.

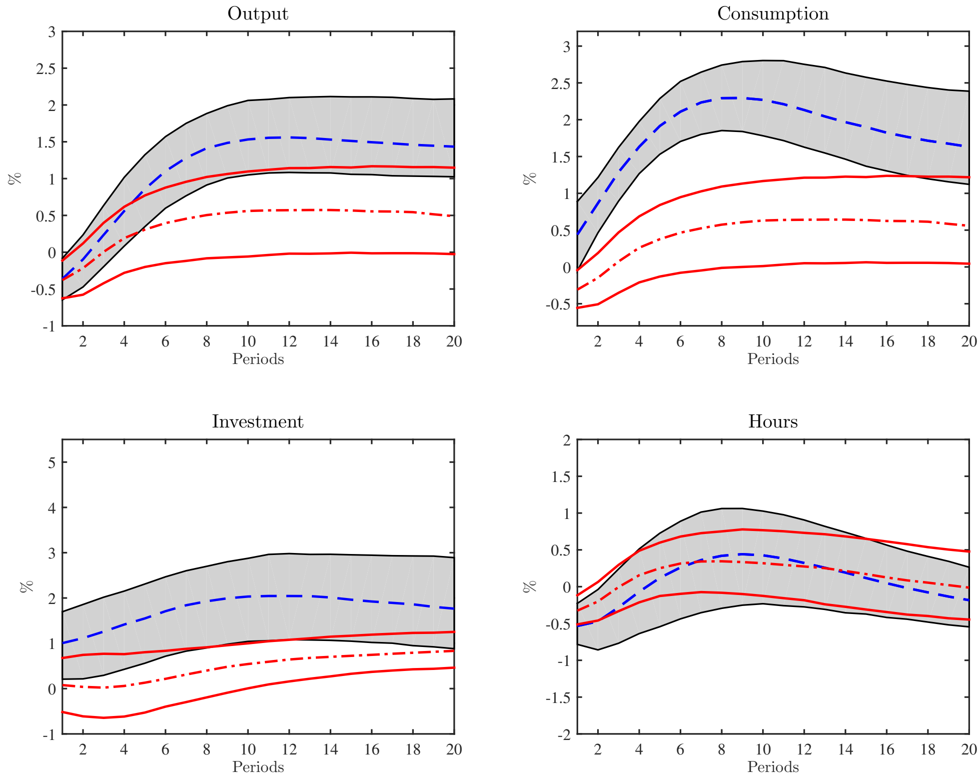
Second, my analysis suggests that a favorable aggregate news shock does not generate comovement among sectoral fundamentals within the two sectors. After a favorable aggregate news shock, hours and output decrease on impact in both sectors. However, differences emerge on consumption and investment. In the durable goods sector, consumption and investment increase; but in the nondurable goods sector, consumption decreases, and investment, remains only barely positive (very close to zero). The lack of comovement within the sectors is in line with that of Barsky and Sims' (2011) finding of no news shock-induced aggregate comovement responses.

The Role of Inventories Having established this difference between the behavior of the two sectors in response to the aggregate news shock, I next turn to the behavior of a variable that can shed some light on the two sectors' contrasting consumption and investment responses. In particular, I focus on the behavior of inventories in the durable goods sector as it has been long understood that the producers of durable goods can use inventories to buffer shocks.[20] This durability feature has potentially important implications on how the sector responds to news shocks. For this reason, I extend my examination of standard fundamentals to include the behavior of a frequently used inventories indicator, the inventories-to-sales ratio (see Blinder and Fischer (1981) and Lovell (1961)).

The view commonly accepted in the literature is that the inventories-to-sales ratio is countercyc-

[20]This is not to say that the nondurable goods sector industries cannot hold stocks of inventories, but simply that inventory volume is much lower than in the durable goods sector industries. For example, the durable goods sector holds more than 70 percent of all manufacturing sector inventories. By definition, "durable" goods producers can also hold inventories for longer periods. The importance of inventories in the durable goods subsector of the manufacturing sector has been recognized and thoroughly discussed in the literature (see Blinder and Holtz-Eakin (1984), Feldstein and Auerbach (1976)).

Figure 4: RESPONSES OF THE SECTORAL FUNDAMENTALS TO A UNIT AGGREGATE NEWS SHOCK

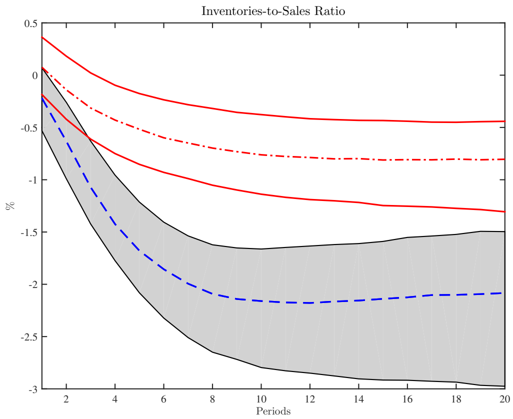


Note: The dashed (durable goods sector) and dash-dotted (nondurable goods sector) lines are the estimated impulse responses to a unit aggregate news shock (BS identification), and correspond to the posterior median estimates. The unit of the vertical axis is the percentage deviation from the situation without a shock. The gray areas and the solid lines represent +/- one standard deviation confidence bands, obtained by drawing from the posterior, in the durable and the nondurable goods sector, respectively.

lical.[21] Firms accumulate their inventories when demand is weak, and liquidate them when demand is high. Also, if there is uncertainty about the sales in the future, firms may hold inventories against the contingency that demand will be unexpectedly high. Therefore, one would expect the inventories-to-sales ratio to decrease when good news about future productivity arrives. My analysis confirms this view. Specifically, in the nondurable goods sector, an aggregate news shock elicits only a very low response of the inventories-to-sales ratio; by contrast, in the durable goods sector, the shock generates a noticeable and significant drop. Figure 5 displays the average responses of the sectoral inventories-to-sales ratios. In the durable goods sector the ratio drops by 2 percent within two years of a news shock; the average response in the nondurables sector is four times smaller. Because the aggregate news shock causes more powerful effects in the durable goods sector, demand grows as consumption of durable goods increases. At the same time, hours drop, in turn diminishing the

[21] For example, Blinder (1981) argues: "The most commonly used indicator of the state of inventory equilibrium or disequilibrium is the ratio of inventories to sales in manufacturing and trade. This ratio moves countercyclically, rising in recessions."

Figure 5: Impulse Responses of Inventories to Sales Ratio to a Unit Aggregate News Shock



Note: The dashed (durable goods sector) and dash-dotted (nondurable goods sector) lines are the estimated impulse responses to a unit aggregate news shock, obtained using the benchmark identification. The responses are from a seven-variable VAR featuring aggregate TFP, consumption, output, hours, stock price index, consumer confidence, and a sectoral inventories-to-sales ratio. The system is estimated in the levels of all variables, features four lags and a constant. The point estimates and confidence bands are obtained as in the case of other sectoral fundamentals.

sector's ability to meet this demand, which itself requires higher production. However, the durable goods sector producers facing this predicament have one channel they can use: they can run down the stock of inventories. This is precisely what my analysis shows.[22]

In what follows I propose a model that can shed light on the transmission mechanism of an aggregate news shock, reconciling theoretical implications with the documented empirical evidence.

4 The Model

This section outlines a two-sector, two-factor, real business cycle model as a theoretical framework to study sectoral business cycles. As in Baxter (1996), sector 1 produces a nondurable consumption good, while sector 2 produces a consumer durable good and the capital good used as an input in the production of both sectors.[23] Another difference between the two sectors is that a good produced in

[22]Since I document an overall larger response of the durable goods sector TFP to an aggregate news shock, there is an implied increase in the relative productivity of the durable and nondurable goods sectors. Hence, one would expect a decline in the relative price of durable goods in response to an aggregate news shock. Furthermore, if consumption for both types of goods occurs on impact, due to a positive wealth effect, the lack of inventories of nondurables could create a scarcity effect that would reinforce the decline in the relative price of durables. When I analyze the response of the relative price of durable goods (the ratio between the durable goods sector and nondurable goods sector consumer price indices) to an aggregate news shock, the above intuition turns out to be correct. In a response to an aggregate news shock, the relative price of durable goods decreases by about 1 percent after just 10 quarters, and then remains at this low level over longer horizons.

[23]Notice that in this type of two-sector real business cycle models, input-output interactions that arise from the usage of intermediate inputs between the sectors, such as in in Hornstein and Praschnik (1997), are limited. Although these interactions are undoubtedly relevant, Christiano and Fitzgerald (1998) explicitly measure their importance using disaggregated data in the nondurable goods sector, casting doubt on the notion that the intermediate good channel is the only reason behind the employment and output comovement between the sectors. Therefore, to fully explore intermediate inputs channel one would need to build on a multi-sector dynamic general equilibrium business

sector 2 can be stocked. In the model, the reason that durable goods are held as stocked inventories, is that inventories are an argument in the production function of sector 2, following Christiano (1988) and Kydland and Prescott (1982). These authors argue that the stock of inventories, as the stock of fixed capital, provides a flow of services to a firm. Here I describe main features of the model.

4.1 Preferences

The economy is populated by a large number of identical, infinitely-lived consumers who derive utility from the consumption of the nondurable consumption good, the service flow from the durable consumption good, and leisure. The representative consumer maximizes lifetime utility, U, defined over sequences of composite consumption, C_t, and hours worked, N_t:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \frac{\left(C_t - \psi N_t^\theta Z_t\right)^{1-\sigma} - 1}{1-\sigma}, \tag{4}$$

where Z_t is a scaling variable given by:

$$Z_t = C_t^\eta Z_{t-1}^{1-\eta}. \tag{5}$$

Preferences are of the type proposed by Jaimovich and Rebelo (2009), which I refer to as JR. When solving the maximization problem, agents internalize the dynamics of Z_t. At the same time, the presence of Z_t makes preferences non-time-separable in consumption and hours worked. Depending on the value of the parameter η, which controls the strength of the wealth effect, these preferences nest as special cases two commonly used types of preferences. In particular, when $\eta = 0$ preferences take the form proposed by Greenwood et al. (1988), which I refer to as GHH. When $\eta = 1$, preferences take the form proposed by King et al. (1988), which I refer to as KPR.[24] The parameter β represents a subjective discount factor, σ is the inverse of the elasticity of intertemporal substitution, θ determines labor supply elasticity, and ψ determines the steady-state level of hours worked. Finally, the composite consumption good, C_t, is given by the constant elasticity of substitution function:

$$C_t = \left[\chi_1 C_{1t}^\mu + \chi_2 C_{2t}^\mu\right]^{\frac{1}{\mu}}, \tag{6}$$

cycle model, such as Horvath (2000), which is beyond the scope of this paper.

[24] Jaimovich and Rebelo (2009) show that these two types of preferences induce qualitatively different responses of the main macroeconomic variables, most importantly hours, to news about future TFP increase. The main characteristic of GHH preferences is that the optimal number of hours worked depends only on the contemporaneous real wage, and therefore news about a future TFP increase produces neither substitution effect, nor a wealth effect on hours. Consequently, hours do not decrease on impact as the result of news. This is not the case with KPR preferences where the optimal number of hours worked responds to changes in lifetime income as well as the current wage. Given good news about future changes in TFP, agents reduce today's supply of labor, because they perceive a higher level of lifetime income, and therefore want to enjoy more leisure.

where C_{1t} and C_{2t} represent period t consumption of the nondurable consumption good and consumption of the service flow from the durable consumption good, respectively, and the parameters χ_1 and χ_2 pin down the weight of the nondurable consumption good in the composite consumption. The elasticity of substitution between the two types of goods depends on the parameter μ, and is given by $1/(1-\mu)$. If the elasticity of substitution is greater than 1 in absolute value, goods are substitutes, whereas, if the elasticity of substitution is less than 1 in absolute value, goods are complements. Finally, the service flow from the durable consumption good is assumed to be proportional to the stock of the durable consumption good S_t:

$$C_{2t} = \gamma S_t, \ \gamma > 0. \tag{7}$$

4.2 Technology

Two final goods are produced in the economy: a perishable consumption good, produced in sector 1, and a capital good, produced in sector 2. A good produced in sector 2 can be used as an investment good in both sectors, as a consumer durable, or can be stocked as inventory. Both sectors use homogenous labor and capital as inputs, but the production of sector 2 requires also inventories. Capital services are modeled as the product of capital stock and the level of capacity utilization. The cost of increasing utilization is additional depreciation of the capital stock. This feature is introduced through the depreciation rate in the two sectors, $\delta_j(u_{jt})$, which I assume to be convex in the rate of utilization: $\delta_j'(u_{jt}) > 0$ and $\delta_j''(u_{jt}) \geq 0$ for $j = 1, 2$. Sector 1's production technology is a standard Cobb-Douglas function:

$$Y_{1t} = F_{1t}\left(K_{1t}, N_{1t}\right) = A_{1t}\left(N_{1t}\right)^{\alpha_1}\left(u_{1t}K_{1t}\right)^{1-\alpha_1}, \tag{8}$$

where N_{1t} and K_{1t} represent sector 1's labor and capital input at time t respectively, u_{1t} represents the rate of capacity utilization in sector 1, A_{1t} represents the technology process in sector 1, and α_1 is the labor's share in this sector. In addition to capital and labor, sector 2 requires also inventories, with the production function given by,

$$Y_{2t} = F_{2t}\left(K_{2t}, N_{2t}, I_t\right) = A_{2t}\left(N_{2t}\right)^{\alpha_2}\left[(1-\rho)\left(u_{2t}K_{2t}\right)^{-\nu} + \rho I_t^{-\nu}\right]^{-\frac{1-\alpha_2}{\nu}}, \tag{9}$$

where N_{2t} and K_{2t} represent labor and capital used in the production of sector 2 output at time t, u_{2t} is the capacity utilization rate in sector 2, I_t denotes the stock of inventories at time t, and α_2 is the labor's share in sector 2.[25] The inclusion of inventory stock into the production function follows

[25]Notice that the durable goods sector TFP measure used in the model (eq. (9)) is slightly different from the one used in the empirical section and referenced by (3), as it does not account for inventories. Notice that the TFP measure in (9) can be rewritten as: $Y_{2t} = A_{2t}\left(N_{2t}\right)^{\alpha_2}\left(u_{2t}K_{2t}\right)^{1-\alpha_2}\left[(1-\rho)+\rho\left(\frac{u_{2t}K_{2t}}{I_t}\right)^{\nu}\right]^{-\frac{1-\alpha_2}{\nu}}$. As noted by Christiano (1988),

Christiano (1988).[26] The parameter ρ controls the role of inventories in the production function of sector 2; if $\rho = 0$ we are back to the standard Cobb-Douglas production function case. Finally, the elasticity of substitution between capital and inventories is $\frac{1}{1+\nu}$; this elasticity is arguably less than one (see Kydland and Prescott (1982)), which is why ν is required to be positive.

Households are assumed to own the physical capital used in both sectors. Labor is assumed to be mobile across sectors; at the same time, I assume adjustment costs that penalize changes in investment and in purchases of new durable goods.[27] The capital stocks in both sectors, K_{1t} and K_{2t}, and the stock of consumer durables, S_t, evolve over time following laws of motion:

$$K_{1,t+1} = (1-\delta_1(u_{1t}))K_{1t} + X_{1t}\left(1-\phi_{x_1}\left(\frac{X_{1t}}{X_{1t-1}}\right)\right), \tag{10}$$

$$K_{2,t+1} = (1-\delta_2(u_{2t}))K_{2t} + X_{2t}\left(1-\phi_{x_2}\left(\frac{X_{2t}}{X_{2t-1}}\right)\right), \tag{11}$$

$$S_{t+1} = (1-\delta_s)S_t + D_t\left(1-\phi_d\left(\frac{D_t}{D_{t-1}}\right)\right), \tag{12}$$

where X_{1t} and X_{2t} denote gross investment in sectors 1 and 2 at time t, while D_t denotes purchases of new consumer durables. The function $\phi_j(\cdot)$ represents the adjustment cost function, which is chosen so that it satisfies the condition of no adjustment costs in the steady state; i.e. $\phi_j(1) = \phi_j'(1) = 0$ for $j = x_1, x_2, d$. Also, $\phi_j'(\cdot), \phi_j''(\cdot) > 0$. This function does not necessarily need to be identical across the sectors, and, therefore, can take different forms.

4.3 Resource Constraints

Since an individual's allocation of time is normalized to 1, hours worked in both sectors cannot exceed total available hours N_t that are equal to $1 - L_t$, where L_t denotes time allocated to leisure at time t. Therefore, a unit of time is allocated as follows:

$$N_{1t} + N_{2t} + L_t \leq 1. \tag{13}$$

for reasonable settings of ρ and ν, the expression in square brackets is close to unity with almost no variance. This is in particular the case for a very small value of ρ that characterizes durable goods sector, that I have used in the theoretical analysis as well. Hence, one can compute the empirical measure of A_{2t} ignoring the term in square brackets altogether.

[26] As Christiano (1988) argues: "all other things being equal, larger inventory stocks probably do augment society's ability to produce goods. For example, spatial separation of the stages of production and distribution, together with economies of scales in transportation, implies that labor inputs can be conserved by transporting goods in bulk and holding inventories." Similarly, Kydland and Prescott (1982) suggest that "with larger inventories, stores can economize on labor resources allocated to restocking." Therefore, adding inventories into the production function seems as a reasonable assumption.

[27] I follow Bernanke (1985), Startz (1989), and Baxter (1996) in assuming that changes in durable goods are subject to adjustment costs.

The resource constraint for the sector producing the pure consumption good and for the sector producing the capital good are, respectively:

$$C_{1t} \leq Y_{1t}, \tag{14}$$

$$D_t + X_{1t} + X_{2t} + \Delta I_t \leq Y_{2t}. \tag{15}$$

4.4 Introducing News Shocks Into the Model

To analyze theoretical effects of news, I introduce a news shock into my model by making reference to my estimates in Section 3. In particular, I follow the approach in Barsky and Sims (2011), and assume that technology processes in the two sectors, denoted by $i \in \{1, 2\}$, are given by,

$$\ln A_{it} = \ln A_{it-1} + g_{it-1} \tag{16}$$

$$g_{it} = \rho_i g_{it-1} + \sigma_i \xi_t. \tag{17}$$

Shock ξ_t can be interpreted as the news shock, given that it has no contemporaneous effect on the level of technology. In particular, as the empirical analysis suggests, the aggregate news shock has different long-run implications on the productivities of the two sectors, but the contemporaneous effects are essentially zero in both sectors. Therefore, this specification, through parameters ρ_i's and σ_i's that are sector-specific, captures well both the almost-identical initial responses and the divergent longer-run responses of the two technology processes in response to the ξ_t shock; although this is a common shock, it propagates differently to the productivities of the two sectors, essentially reflecting different sector-specific information contained in the news about aggregate productivity prospects.[28] The resulting theoretical responses will be a smooth version of a commonly used theoretical responses of technology to news shocks.[29] In particular, productivity processes start slowly to increase after the initial period, allowing the shock to slowly diffuse into the economy. Since this is a perfect information framework, households immediately learn the expected future path of technology processes in the two sectors and adjust their responses accordingly.

Since both technology processes feature a stochastic trend, with possibly different growth rates, the model needs to be made stationary. In particular, I will make use of the fact that along the balanced growth path several ratios need to be stationary: ratio of nondurable consumption and

[28]The assumption that there is a common component in sectoral TFPs aims to capture, admittedly in reduced form, unmodeled potential source of comovements across sectors, such as input-output linkages in intermediate production, or common production inputs, as investigated by Kim and Kim (2006). This assumption is supported by evidence that productivity across industries is quite correlated, as pointed out by Costello (1993).

[29]In a commonly used approach, the economy is assumed to be in the steady state in period 0, when a signal arrives suggesting that a positive technology shock will occur in s periods. Therefore, productivity process remains at its steady-state level until period s, when the increase is realized. TFP then rises by 1 percent and follows its exogenous law of motion afterwards. This string of literature, however, is mostly concerned with qualitative predictions, and therefore obtaining smooth responses is not essential.

output, ratio of new durable purchases and durable output, ratio of investment in both nondurable and durable goods and durable output, as well as the ratio of a change in inventories and durable goods sector output.

5 Calibration and Functional Forms

I calibrate most of the structural parameters of the model in a standard fashion. Table 1 reports the values of all the parameters in the benchmark model, and below I describe reasoning behind this choice.

The time unit is defined to be a quarter. The value of the subjective discount factor β, is chosen to be consistent with an annual real interest rate of 4 percent. Composite-consumption parameters, χ_1 and χ_2, are calibrated such that the steady-state shares of nondurable goods in the composite consumption equal the average over the sample period, which is 0.723. As mentioned before, I use JR preferences, with 0.027 as the benchmark value for η; this value implies a low wealth effect. The inverse of the elasticity of intertemporal substitution, σ, is quite standard and is equal to 2. The parameter μ controls the elasticity of substitution between the two consumption goods, and is calibrated to the value that corresponds to the elasticity of 1.5, as in Baxter (1996). The preference parameter ψ is chosen so that the agents allocate one third of their time endowment to work. As in Jaimovich and Rebelo (2009), θ is set to 1.4, which corresponds to aggregate labor supply elasticity of 2.5 when preferences are GHH.

The labor share coefficients, α_1 and α_2, are chosen to match the mean of labor's share in the two sectors over the sample period. The parameter ρ, which determines the role of inventories in the production function of sector 2, is chosen to match the steady-state share of inventories in output. Since parameter ν, which controls the elasticity of substitution in production between capital and inventories, is hard to measure empirically, I choose the value that implies the elasticity of substitution between capital services and inventories used by Christiano (1988).

Depreciation rate takes the form: $\delta_j\left(u_{jt}\right) = \delta_{j0} + \delta_{j1}\left(u_{jt}-1\right) + \frac{\delta_{j2}}{2}\left(u_{jt}-1\right)^2$, with $\delta_{j0}, \delta_{j1}, \delta_{j2} > 0$ and $j = 1,2$ corresponding to the two sectors. Following Bernanke (1985) and Baxter (1996), annual capital depreciation rates in the two sectors are 7.1 percent, and the annual depreciation rate of the stock of durables, δ_s, is 15.6 percent. The parameters δ_1^1 and δ_1^2 are calibrated to ensure that steady-state capacity utilizations in both sectors, u_1 and u_2, equal unity. Since there is little guidance in the literature about appropriate values of δ_{j2}'s, I choose the values that would imply the cost of utilization with respect to the rate of utilization in both sectors to be 0.15, which is the value used by Jaimovich and Rebelo (2009).

The adjustment cost function takes the form: $\phi_j = \frac{\kappa_j}{2}\left(\frac{Z_{jt}}{Z_{jt-1}}-1\right)^2$, where $\kappa_j > 0$ with $j = 1,2,d$ and $Z_{jt} = X_{1t}, X_{2t}, D_t$. This specification implies that adjustment costs are not incurred in

Table 1: VALUES OF THE MODEL PARAMETERS

Parameter	Value	Description
β	0.9902	Subjective discount factor
γ	0.7	Service flow from durables
α_1	0.60	Labor share in the nondurable goods sector
α_2	0.67	Labor share in the durable goods sector
$\delta_{1,0}$	1.73%	Steady-state depreciation rate in the nondurable goods sector
$\delta_{2,0}$	1.73%	Steady-state depreciation rate in the durable goods sector
$\delta_{S,0}$	3.58%	Depreciation rate of the stock of durables
$\delta_{1,2}/\delta_{1,1}$	0.15	Elasticity of utilization cost wrt utilization rate in the nondurable goods sector
$\delta_{2,2}/\delta_{2,1}$	0.15	Elasticity of utilization cost wrt utilization rate in the durable goods sector
ρ	$3 * 10^{-5}$	Parameter with inventories in the production function
μ	0.33	Determines elasticity of substitution between nondurable and durable consumption goods
θ	1.4	Utility function parameter with labor
$\bar{N}$	0.30	Steady-state level of hours worked, controlled by ψ
η	0.027	Utility function parameter that controls wealth effect
σ	2	Intertemporal elasticity of substitution
ν	3.671	Elasticity of substitution between inventories and capital
κ_1	25	Sector 1 investment adjustment cost function parameter
κ_2	20	Sector 2 investment adjustment cost function parameter
κ_S	2	Stock of durables adjustment cost function parameter
ρ_1	0.5	Sector 1 technology persistence parameter
σ_1	0.65	Sector 1 technology volatility parameter
ρ_2	0.12	Sector 2 technology persistence parameter
σ_2	0.25	Sector 2 technology volatility parameter

maintaining the steady state levels of capital and consumer durables.

6 Results

One-sector model For a long time, the news literature was faced with the challenge of building a model that can generate Pigou cycles, a comovement between consumption, hours, output, and investment, in response to news about higher future TFP. The notion that comovement is generated by news at first was supported only by anecdotal evidence or a general belief that aggregate variables should comove in response to positive news. Beaudry and Portier (2006) were the first authors to identify technological news shocks and show that they lead to a comovement between aggregate variables. The comovement, however, was at odds with the predictions of a standard RBC model with KPR preferences, which is why the attention of the literature turned towards obtaining theoretical comovements.[30] For example, Jaimovich and Rebelo (2009) formulate a one-sector model that is able to generate Pigou cycles, stressing that having preferences that induce no wealth effect on leisure/labor when news is received is crucial for the result. However, using a different, and arguably more vigorous identification strategy than the one originally proposed, Barsky and Sims (2011) document that aggregate variables actually do not comove in response to a positive news shock. This result implied that all the proposed modifications of a standard model had not been required in the

[30]Standard RBC model with KPR preferences fails to reproduce a comovement since good news increases consumption and leisure on impact through the wealth effect. Since leisure increases, hours worked and output decrease. The only way for consumption and hours (or output) to move in opposite directions is through a decrease in investment. Many authors have tried to "fix" this problem by proposing various features that can help a one-sector model to generate comovement (see Beaudry and Portier (2004), Den Haan and Kaltenbrunner (2009), Jaimovich and Rebelo (2009)).

first place, as the observed empirical facts would have been easily generated by a standard one-sector RBC model with KPR preferences.

Two-sector model Following the benchmark strategy I show that, analogously to the aggregate level, comovement is not present at the sectoral level either. A positive aggregate news shock leads to similar responses in some respects: in both sectors, investment responses are positive, and hours and output responses are negative. But the consumption responses are the opposite: positive for the durable goods sector, and negative for the nondurable goods sector. Generating a negative response of aggregate hours in a one-sector RBC model with standard KPR preferences is straightforward because of the large wealth effect on leisure/labor when news is received, but generating a negative response of hours in both sectors at the same time represents a more challenging task. In particular, comovement between hours in the durable and nondurable goods sectors cannot be obtained with KPR preferences. I briefly describe the intuition behind this result.

From the first order conditions with respect to hours and consumption in the nondurable goods sector with KPR preferences, it is straightforward to obtain:

$$\begin{aligned}\psi\theta N_t^{\theta-1} &= A_{1t}\alpha_1\frac{C_{1t}}{N_{1t}}\frac{1}{C_t}\frac{\partial C_t}{\partial C_{1t}},\\ \psi\theta N_t^{\theta-1} &= A_{1t}\alpha_1\frac{1}{N_{1t}}\frac{\chi_1 C_{1t}^{\mu}}{\chi_1 C_{1t}^{\mu}+\chi_2 C_{2t}^{\mu}}.\end{aligned} \tag{18}$$

Since consumption of the durable good cannot change on impact as it is a function of the stock of durables, S_t, which is a predetermined variable, C_{1t} is the only channel through which C_t can change. Therefore, the right hand side of equation (18) essentially boils down to $A_{1t}\alpha_1\frac{1}{N_{1t}}$, which, together with the constraint (13), implies that N_{1t} and N_{2t} cannot move in the same direction on impact.

The analogous equation with GHH preferences is:

$$\begin{aligned}\psi\theta N_t^{\theta-1} &= A_{1t}\alpha_1\frac{C_{1t}}{N_{1t}}\frac{\partial C_t}{\partial C_{1t}},\\ \psi\theta N_t^{\theta-1} &= A_{1t}\alpha_1\frac{1}{N_{1t}}\frac{[\chi_1 C_{1t}^{\mu}+\chi_2 C_{2t}^{\mu}]^{\frac{1}{\mu}}\chi_1 C_{1t}^{\mu}}{\chi_1 C_{1t}+\chi_2 C_{2t}}.\end{aligned} \tag{19}$$

Again, since the change in the composite consumption C_t can come only from changes in C_{1t}, the right hand side of equation (19) essentially boils down to $A_{1t}\alpha_1\frac{\chi_1^{1/\mu}C_{1t}^{\mu}}{N_{1t}}$, which shows that it is possible for N_{1t} and N_{2t} to move in the same direction; this is because of the presence of the demand channel, represented by changes in C_{1t}.

A similar point has been made by Jaimovich and Rebelo (2009), who investigate comovement in a two-sector model which features consumption and investment goods. Although their model and mine differ in several dimensions, they show that preferences that feature very low wealth effect are necessary to obtain comovement. However, as most of the literature at the aggregate level, they start from the premise that after a positive news shock hours in the two sectors should increase as well as consumption, output and investment. In Section 3, I showed that this premise, when the manufacturing sector is considered, is not supported empirically and that a positive news shock induces hours worked in both sectors to decrease on impact. Generating both comovement of hours worked across the two sectors and simultaneous negative responses on impact represents a challenging task. This is because in response to a positive shock, with preferences that feature small wealth effect, hours worked would generally not change or slightly increase on impact, as shown by Jaimovich and Rebelo (2009).

While preferences with very low or zero wealth effect, such as GHH preferences, are necessary for obtaining a comovement between sectoral hours, generating negative impact responses of hours in both sectors at the same time requires additional features. Specifically, motivated by my empirical analysis, I show that adding inventories can help my model in two dimensions. First, it can help the model obtain this negative response of hours in both sectors on impact. Second, this channel can also help my model replicate comovement between consumption and investment observed in the durable goods sector, since holding stocks of inventories is one way that the durable goods sector producers can meet higher consumer demand without necessarily having to decrease investment.

6.1 Model Predictions

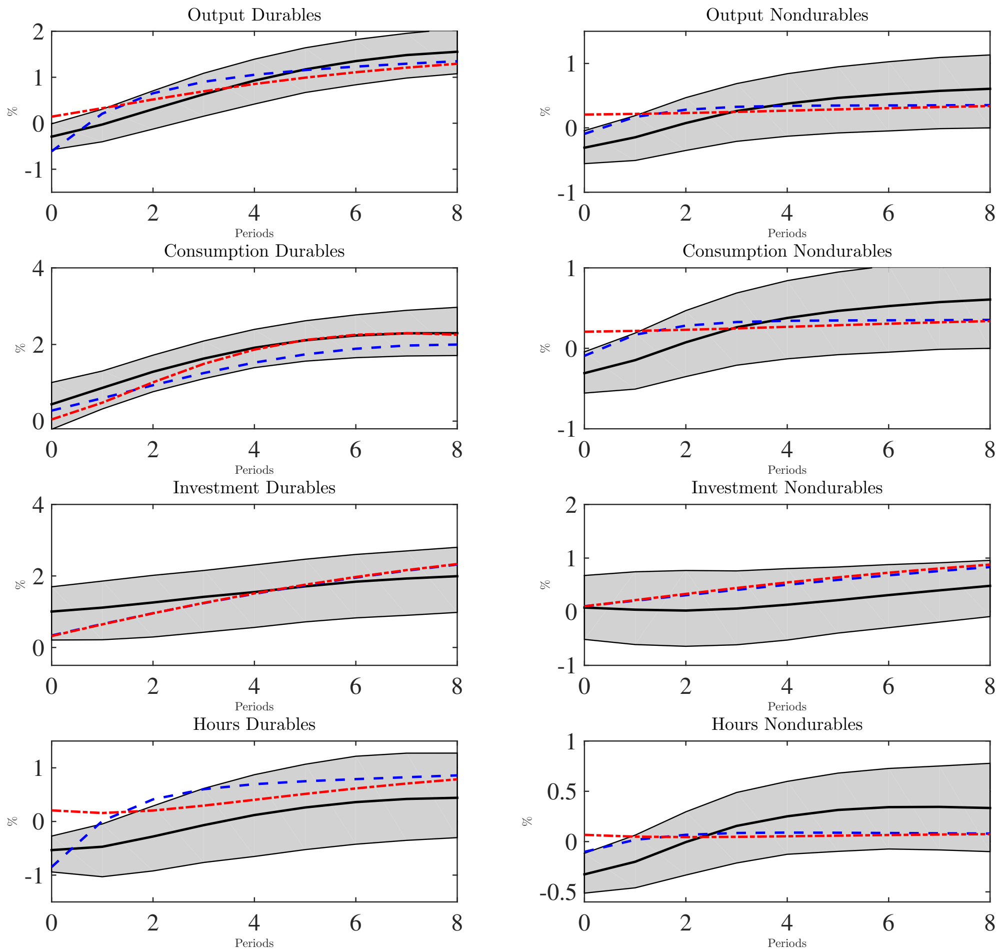
Figure 6 displays theoretical and empirical responses of sectoral outputs, consumptions, investments and hours to a unit aggregate news shock. The empirical responses (black solid lines) and confidence regions (shaded gray areas) are the ones implied by the benchmark identification scheme from Figure 4, while the theoretical responses are computed using the model described in Section 4. As discussed above, because adding inventories can help my model in several dimensions, here I report the responses implied by the benchmark model with inventories (blue dashed lines) and without inventories (red dash-dotted lines).[31]

The model without inventories is consistent with the view that news generates comovement among all variables in both sectors of the economy. The only way that sectoral outputs can change on impact in this model is through changes in the sectoral supply of labor and in the rates of capacity utilization. Capacity utilization increases as the presence of investment adjustment costs makes investment increase, decreasing the value of installed capital in both sectors. Higher capacity utilization increases the marginal product of labor in both sectors, which induces agents to increase their labor supply. Given the low wealth effect needed for obtaining comovement of sectoral hours, this increase in the supply of labor together with higher capital utilization rates translates into increases of output in both sectors. In the nondurable goods sector, higher output would satisfy higher consumption

[31] A standard production function without inventories is obtained by setting the parameter ρ in the production function to zero. At the same time, inventories are not present in (15).

for nondurable goods while, in the durable goods sector, higher output would be enough to satisfy increased demand for investment goods and for the purchases of new durable goods. However, the view that news generates both aggregate and sectoral comovement does not have a solid empirical justification. In particular, I showed that a positive aggregate news shock does not generate sectoral comovement because it leads to positive investment responses in both sectors; negative responses of hours and output in both sectors; and contrasting sectoral consumption responses, positive for durable goods and negative or nondurable goods. Since the short-run predictions of this model are clearly at odds with the empirical predictions, additional features are needed to explain empirically observed behavior.

Figure 6: Empirical and Model Implied Impulse Responses to an Aggregate News Shock



Note: The dashed and dash-dotted lines are the model implied impulse responses to a unit aggregate news shock. Dashed blue lines represent responses from the benchmark model and dash-dotted red lines represent responses from the same model, but without inventories. The unit of the vertical axis is the percentage deviation from the situation without a shock. The black solid lines represent empirical responses implied by the benchmark specification, while gray areas correspond to the +/- one standard deviation confidence bands.

Adding inventories in the production of the durable goods proves to be the feature that brings the short-run predictions of the model much closer to the empirical ones. First, the model with inventories can replicate the negative impact responses of hours in both sectors. In fact, contrary to the situation when inventories are not present in the model, utilization rates decrease on impact in both sectors, especially in the durable goods sector. The intuition for this result is as follows: in the presence of adjustment costs incurred with changes in sectoral investment and purchases of new durable goods it is optimal to smooth both sectoral investment and purchases of new durables over time; therefore, both investment and purchases of new durable goods increase on impact. This observation holds regardless of the presence of inventories in the model. However, the presence of inventories will affect how utilization of capital in the durable goods sector adjusts in order to meet this increased investment demand. In particular, since inventories represent one additional margin through which this increased demand can be met, the optimal response will be to run down inventories in the short run. Anticipating this fact, given that capital and inventories are complementary in production, it is optimal to decrease capital utilization rate in the durable goods sector. This decrease in utilization rate decreases the marginal product of labor, inducing agents to decrease labor supply in the durable goods sector. At the same time, because of the low wealth effect decreases in the labor supply occur in both sectors. Lower labor supply, together with lower utilization rates, leads to a decline in output in both sectors. As output in the nondurable goods sector decreases, so does nondurables consumption. However, because the durable goods sector can hold inventories, as output decreases in this sector, both consumption and investment can increase at the same time as the stock of inventories adjusts to meet higher demand for new purchases of durable consumption goods as well as for investment goods used in the production of the two sectors.

The model performs remarkably well in replicating sector-specific responses to an aggregate news shock not only on impact but also over longer horizons. First, it correctly predicts that the responses in the durable goods sector are larger than those in the nondurable goods sector. Part of this result comes from the fact that the expected productivity increase is higher in the durable goods sector, and part of it comes from the presence of an endogenous accelerator mechanism as the investment good is used in the production of both sectors of the economy. Second, all of the theoretical impulse response functions are contained within the confidence bands. Although the model underestimates the point response of the labor supply and therefore output in the nondurable goods sector, it can still predict negative responses that are contained within the confidence intervals.

As an additional check of the benchmark model, I also evaluate how well it matches sectoral business cycles. Namely, Table 2 compares the cyclical volatility of the key variables in the model to that in the data. Both the model simulated data and the U.S. data have been filtered with the Hodrick and Prescott (1997) filter with the smoothing parameter $\lambda = 1600$. The model correctly predicts that output, consumption, investment and hours are more volatile in durables than in nondurables. In particular, the model features investment, consumption and output that are about twice as volatile in durables as investment, consumption and output in nondurables, which is quite similar to the data. Second, the model is able to correctly predict relative volatilities within sectors, with the exception of hours in the nondurable goods sector, where volatility is underestimated with respect to the data. Nevertheless, the model captures the general feature of higher volatility of hours in the durables than in nondurables. For the inventories measure, the model predicts volatility that is very close to that found in the data. That the benchmark model performs quite well also along this dimension is reassuring.

Table 2: Empirical and Model Business Cycles

	Data		Benchmark Model	
	Durables	Nondurables	Durables	Nondurables
Output	5.10	2.47	5.83	2.52
Consumption	4.39	2.24	4.37	2.52
Investment	6.56	4.04	6.13	2.58
Hours	4.88	2.31	6.64	1.29
Inventories	3.59	1.38	3.29	-

Note: This table reports empirical and model-implied business-cycle standard deviations. Both data and model variables are logged and HP filtered ($\lambda = 1600$).

6.2 Robustness

The ingredients of the model that are crucial for obtaining the above results are: inventories in the production of durable goods, preferences with low wealth effect, adjustment costs in investment, adjustment costs in new purchases of durable goods, and variable capacity utilization.

Using variable capital utilization is in line with the empirical measure of capital used in Section 3. From a theoretical perspective, variable utilization serves an important function of creating a channel through which hours can respond to a news shock when adjustment costs are positive. The results are robust for relatively wide range of the elasticities of the cost of utilization with respect to the rate of utilization, $\delta_j''(u_j)u_j/\delta_j'(u_j)$ with $j = 1, 2$. In particular, while the utilization-cost elasticity in the durable goods sector, $\delta_2''(u_2)u_2/\delta_2'(u_2)$, can take very high values, results are more sensitive to the elasticity in the nondurable goods sector, which needs to be $\delta_1''(u_1)u_1/\delta_1'(u_1) < 1.2$.

Preferences that feature low wealth effect are crucial for obtaining instantaneous comovement of hours in the two sectors. The strength of the wealth effect is controlled by the parameter η; when $\eta = 1$ comovement between hours in the two sectors on impact is not possible, while it is possible for $\eta = 0$. Therefore, it is clear that the strength of the wealth effect will have an important role in determining impact responses of hours in both sectors. In the benchmark model $\eta = 0.027$, implying a low wealth effect. Nevertheless, the results are robust for the values of $\eta \in (0, 0.15)$. While having inventories is enough to obtain the negative response of hours in the durable goods sector, a small positive value of η is needed to generate the comovement of hours in the two sectors. An additional, more technical, reason why preferences with a small wealth effect are needed is that they are consistent with the balanced growth path.[32] Another parameter that is relevant for the results is the labor supply elasticity, θ, which needs to take values $\theta < 1.6$.[33]

Adjustment costs are needed to obtain observed initial positive responses of investment and a positive response of new purchases of durable goods. It is enough to have κ_1, κ_2 and κ_s greater than zero to obtain positive response on impact.

The model also works very well along the dimension of matching the response of inventories. That my model works well in this dimension is encouraging, particularly since it is able to replicate the response of a variable which, as mentioned above, is relevant for understanding differing extent to which news shocks are propagated in durable and nondurable goods sectors. The parameter ρ, which controls the importance of inventories in the production function, is set to match the long-run ratio of inventories to output, and is therefore calibrated to a very low number as previously discussed. To be consistent with the suggestion by Kydland and Prescott (1982) that capital and inventories are somewhat complementary in production, values of ν must be greater than one. In fact, my results are robust for the values of $\nu > 1$ because they rely on the complementarity between capital and inventories in production.

I thus conclude that by examining a model with distinct durable and nondurable goods sectors, with an explicit role for inventories, and with plausible parameter values, I am able to replicate key characteristics of the sectoral empirical responses of the economy to aggregate news about future productivity.

7 Conclusions

This paper argues that an aggregate news shock represents a durable-goods-sector news shock. This shock then propagates mainly through the durable goods sector of the economy, primarily affecting durable-goods-sector fundamentals. This paper also challenges the anecdotal view that there is sectoral comovement among hours, consumption, investment and output after a positive aggregate news shock. By using an identification strategy widely accepted in the literature, I show that positive aggregate news shock does not in fact generate comovement across or within the nondurable and durable goods sectors, as previously thought. Given that sectoral comovement is one of the central features of the business cycles, these results suggest that aggregate news shocks cannot be the main driving force of the short-run sectoral dynamics. In addition, my empirical investigation of

[32]Preferences that feature zero wealth effect, such as GHH preferences, are not consistent with the balance growth path unless some additional features, such as a trend in the utility function that would make utility cost of supplying labor increase at the same rate as the real wage, are added into a model.

[33]This result is consistent with that of Jaimovich and Rebelo (2009) where they need a responsive labor supply to generate sectoral comovement.

inventories, an important margin that durable goods producers can use to buffer news shocks, shows that inventories represent an important propagation channel of the news shock.

Squaring this empirical evidence with a standard two-sector model with KPR preferences would be nearly impossible. Therefore, this paper proposes a two-sector model that matches empirical findings remarkably well; the model features low short-run wealth effect on labor supply, adjustment costs in investment, adjustment costs in purchases of new durable goods, and the durable goods sector production that requires inventories. The last feature proves to be a crucial feature for obtaining simultaneous negative initial responses of hours in both sectors, as well as for obtaining the comovement of investment and consumption in the durable goods sector despite the fall in output. The low wealth effect is the feature of the model that is important for obtaining comovement between hours and, therefore, comovement between outputs in the two sectors.

References

Barsky, R. B. and E. R. Sims (2011): "News shocks and business cycles," *Journal of Monetary Economics*, 58, 273–289.

Basu, S. and J. G. Fernald (1994): "Constant returns and small markups in U.S. manufacturing," International Finance Discussion Papers 483, Board of Governors of the Federal Reserve System (U.S.).

Baxter, M. (1996): "Are Consumer Durables Important for Business Cycles?" *The Review of Economics and Statistics*, 78, 147–55.

Beaudry, P. and B. Lucke (2010): "Letting Different Views about Business Cycles Compete," in *NBER Macroeconomics Annual 2009, Volume 24*, National Bureau of Economic Research, Inc, NBER Chapters, 413–455.

Beaudry, P., D. Nam, and J. Wang (2011): "Do Mood Swings Drive Business Cycles and is it Rational?" NBER Working Papers 17651, National Bureau of Economic Research, Inc.

Beaudry, P. and F. Portier (2004): "An exploration into Pigou's theory of cycles," *Journal of Monetary Economics*, 51, 1183–1216.

——— (2006): "Stock Prices, News, and Economic Fluctuations," *American Economic Review*, 96, 1293–1307.

——— (2014): "News-Driven Business Cycles: Insights and Challenges," *Journal of Economic Literature*, 52, 993–1074.

Ben Zeev, N. and H. Khan (2015): "Investment-Specific News Shocks and U.S. Business Cycles," *Journal of Money, Credit and Banking*, 47, 1443–1464.

Bernanke, B. (1985): "Adjustment costs, durables, and aggregate consumption," *Journal of Monetary Economics*, 15, 41–68.

Bils, M. and J. A. Kahn (2000): "What Inventory Behavior Tells Us about Business Cycles," *American Economic Review*, 90, 458–481.

Blinder, A. S. (1981): "Retail Inventory Behavior and Business Fluctuations," *Brookings Papers on Economic Activity*, 12, 443–520.

——— (1986): "Can the Production Smoothing Model of Inventory Behavior Be Saved?" *The Quarterly Journal of Economics*, 101, 431–53.

Blinder, A. S. and S. Fischer (1981): "Inventories, rational expectations, and the business cycle," *Journal of Monetary Economics*, 8, 277–304.

Blinder, A. S. and D. Holtz-Eakin (1984): "Inventory Fluctuations in the United States Since 1929," NBER Working Papers 1371, National Bureau of Economic Research, Inc.

Burnside, C. (1996): "Production function regressions, returns to scale, and externalities," *Journal of Monetary Economics*, 37, 177–201.

Burnside, C., M. Eichenbaum, and S. Rebelo (1995): "Capital Utilization and Returns to Scale," in *NBER Macroeconomics Annual 1995, Volume 10*, National Bureau of Economic Research, Inc, NBER Chapters, 67–124.

Christiano, L. J. (1988): "Why does inventory investment fluctuate so much?" *Journal of Monetary Economics*, 21, 247–280.

Christiano, L. J. and M. Eichenbaum (1987): "Temporal aggregation and structural inference in macroeconomics," *Carnegie-Rochester Conference Series on Public Policy*, 26, 63–130.

Christiano, L. J. and T. J. Fitzgerald (1998): "The business cycle: it's still a puzzle," *Economic Perspectives*, 56–83.

Costello, D. M. (1993): "A Cross-Country, Cross-Industry Comparison of Productivity Growth," *Journal of Political Economy*, 101, 207–22.

Crouzet, N. and H. Oh (2016): "What do inventories tell us about news-driven business cycles?" *Journal of Monetary Economics*, 79, 49–66.

Den Haan, W. J. and G. Kaltenbrunner (2009): "Anticipated growth and business cycles in matching models," *Journal of Monetary Economics*, 56, 309–327.

Eichenbaum, M. S. (1984): "Rational expectations and the smoothing properties of inventories of finished goods," *Journal of Monetary Economics*, 14, 71–96.

Feldstein, M. and A. Auerbach (1976): "Inventory Behavior in Durable-Goods Manufacturing: The Target-Adjustment Model," *Brookings Papers on Economic Activity*, 7, 351–408.

Fernald, J. G. (2012): "A quarterly, utilization-adjusted series on total factor productivity," Tech. Rep. 2012-19, Federal Reserve Bank of San Francisco.

Fisher, J. D. M. (2010): "Comment on "Letting Different Views about Business Cycles Compete"," in *NBER Macroeconomics Annual 2009, Volume 24*, National Bureau of Economic Research, Inc, NBER Chapters, 457–474.

Fisher, J. D. M. and A. Hornstein (2000): "(S, s) Inventory Policies in General Equilibrium," *Review of Economic Studies*, 67, 117–145.

Forni, M., L. Gambetti, and L. Sala (2014): "No News in Business Cycles," *Economic Journal*, 124, 1168–1191.

Francis, N., M. T. Owyang, J. E. Roush, and R. DiCecio (2014): "A Flexible Finite-Horizon Alternative to Long-Run Restrictions with an Application to Technology Shocks," *The Review of Economics and Statistics*, 96, 638–647.

Görtz, C. and J. D. Tsoukalas (2017): "News and Financial Intermediation in Aggregate Fluctuations," *The Review of Economics and Statistics*, 99, 514–530.

Görtz, C., J. D. Tsoukalas, and F. Zanetti (2016): "News Shocks under Financial Frictions," Working Papers 2016: 15, Business School - Economics, University of Glasgow.

Greenwood, J., Z. Hercowitz, and G. W. Huffman (1988): "Investment, Capacity Utilization, and the Real Business Cycle," *American Economic Review*, 78, 402–17.

Hamilton, J. (1994): *Time series analysis*, Princeton, NJ: Princeton Univ. Press.

Hodrick, R. J. and E. C. Prescott (1997): "Postwar U.S. Business Cycles: An Empirical Investigation," *Journal of Money, Credit and Banking*, 29, 1–16.

Hornstein, A. and J. Praschnik (1997): "Intermediate inputs and sectoral comovement in the business cycle," *Journal of Monetary Economics*, 40, 573–595.

Horvath, M. (2000): "Sectoral shocks and aggregate fluctuations," *Journal of Monetary Economics*, 45, 69 – 106.

Jaimovich, N. and S. Rebelo (2009): "Can News about the Future Drive the Business Cycle?" *American Economic Review*, 99, 1097–1118.

Kahn, J. A. (2008a): "Durable goods inventories and the Great Moderation," Staff Reports 325, Federal Reserve Bank of New York.

——— (2008b): "What drives housing prices?" Staff Reports 345, Federal Reserve Bank of New York.

Khan, H. and J. Tsoukalas (2012): "The Quantitative Importance of News Shocks in Estimated DSGE Models," *Journal of Money, Credit and Banking*, 44, 1535–1561.

Kim, Y. S. and K. Kim (2006): "How Important is the Intermediate Input Channel in Explaining Sectoral Employment Comovement over the Business Cycle?" *Review of Economic Dynamics*, 9, 659–682.

King, R. G., C. I. Plosser, and S. T. Rebelo (1988): "Production, growth and business cycles: II. New directions," *Journal of Monetary Economics*, 21, 309–341.

Kryvtsov, O. and V. Midrigan (2013): "Inventories, Markups, and Real Rigidities in Menu Cost Models," *Review of Economic Studies*, 80, 249–276.

Kurmann, A. and E. Mertens (2014): "Stock Prices, News, and Economic Fluctuations: Comment," *American Economic Review*, 104, 1439–45.

Kurmann, A. and C. Otrok (2013): "News Shocks and the Slope of the Term Structure of Interest Rates," *American Economic Review*, 103, 2612–32.

Kydland, F. E. and E. C. Prescott (1982): "Time to Build and Aggregate Fluctuations," *Econometrica*, 50, 1345–70.

Long, John B, J. and C. I. Plosser (1983): "Real Business Cycles," *Journal of Political Economy*, 91, 39–69.

Lovell, M. (1961): "Manufacturers' Inventories, Sales Expectations, and the Acceleration Principle," *Econometrica*, 29, pp. 293–314.

Mankiw, N. G. (1985): "Consumer Durables and the Real Interest Rate," *The Review of Economics and Statistics*, 67, 353–62.

Nam, D. and J. Wang (2014): "Are predictable improvements in {TFP} contractionary or expansionary: Implications from sectoral TFP?" *Economics Letters*, 124, 171 – 175.

Pigou, A. (1927): *Industrial Fluctuations*, London: MacMillan.

Ramey, V. A. (1989): "Inventories as Factors of Production and Economic Fluctuations," *American Economic Review*, 79, 338–54.

Rebelo, S. (2005): "Real Business Cycle Models: Past, Present and Future," *Scandinavian Journal of Economics*, 107, 217–238.

Schmitt-Grohé, S. and M. Uribe (2012): "What's news in business cycles," *Econometrica*, 80, 2733–2764.

Startz, R. (1989): "The Stochastic Behavior of Durable and Nondurable Consumption," *The Review of Economics and Statistics*, 71, 356–63.

Theodoridis, K. and F. Zanetti (2016): "News shocks and labour market dynamics in matching models," *Canadian Journal of Economics*, 49, 906–930.

Uhlig, H. (2004): "What moves GNP?" Econometric Society 2004 North American Winter Meetings 636, Econometric Society.

A Identification of News Shocks

For comprehensiveness, in this section I describe the benchmark identification procedure used in this paper, proposed by Barsky and Sims (2011). In doing so, I rely heavily on the notations used in the original article. This procedure starts from the assumption that aggregate technology is driven by two uncorrelated shocks: traditional contemporaneous technology shock and a news shock, which agents observe in advance. Since it would be impossible to uniquely identify these two innovations in a univariate setting (when relying only on the observed technology series), the news shock must be identified by extracting information from the movements in forward-looking variables, such as stock prices or consumer confidence, for example.

Start from the moving average representation of a reduced-form VAR:

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t$$

where $\mathbf{y_t}$ is an $(n \times 1)$ vector of observables at time t, $t = 1, \ldots, T$, $\mathbf{B}(\mathbf{L})$ is a lag order polynomial, and $\mathbf{u}_t \sim i.i.d\, N(\mathbf{0}, \mathbf{\Sigma})$.

At the same time, assume that there exists a linear mapping between the reduced-form innovations and structural shocks, ε_t, given by: $\mathbf{u}_t = \mathbf{A_0}\varepsilon_t$. The structural moving average representation is then:

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\varepsilon_t,$$

with $\mathbf{C}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\mathbf{A}_0$ and $\varepsilon_t = \mathbf{A}_0{}^{-1}\mathbf{u}_t$. The impact matrix must satisfy $\mathbf{A}_0\mathbf{A}_0' = \mathbf{\Sigma}$. This matrix is not unique because for any matrix $\mathbf{A}_0$ there exists a matrix $\widetilde{\mathbf{A}_0}$ such that $\widetilde{A_0}\mathbf{D} = \mathbf{A}_0$, with $\mathbf{D}$ being an $(n \times n)$ orthonormal matrix, that also satisfies the above criterion, i.e. $\widetilde{\mathbf{A}_0}\widetilde{\mathbf{A}_0}' = \mathbf{\Sigma}$. The identification of structural shocks, therefore, consists of finding a mapping, $\mathbf{A}_0$, between innovations and structural shocks.

To understand the logic behind the identification, denote h step ahead forecast error as:

$$\mathbf{y}_{t+h} - E_{t-1}\mathbf{y}_{t+h} = \sum_{\tau=0}^{h} \mathbf{B}_\tau \widetilde{\mathbf{A_0}}\mathbf{D}\varepsilon_{t+h-\tau}.$$

Then, the share of the forecast error variance of variable i attributable to structural shock j at horizon h is given by:

$$\begin{aligned}\Omega_{i,j}(h) &= \frac{\mathbf{e}_i'\left(\sum\limits_{\tau=0}^{h} \mathbf{B}_\tau \widetilde{\mathbf{A_0}}\mathbf{D}\mathbf{e}_j\mathbf{e}_j'\mathbf{D}'\widetilde{\mathbf{A_0}}'\mathbf{B}_\tau'\right)\mathbf{e}_i}{\mathbf{e}_i'\left(\sum\limits_{\tau=0}^{h} \mathbf{B}_\tau \mathbf{\Sigma}\mathbf{B}_\tau'\right)\mathbf{e}_i} \\ &= \frac{\sum\limits_{\tau=0}^{h} \mathbf{B}_{i,\tau}\widetilde{\mathbf{A_0}}\mathbf{D}_j\mathbf{D}_j'\widetilde{\mathbf{A}_0}'\mathbf{B}_{i,\tau}'}{\sum\limits_{\tau=0}^{h} \mathbf{B}_{i,\tau}\mathbf{\Sigma}\mathbf{B}_{i,\tau}'},\end{aligned}$$

where $\mathbf{e}_i$ is a column vector with the 1 in the ith place and zeros elsewhere. The vector e_j, then, picks out the j^{th} column of $\mathbf{D}$, denoted by $\mathbf{D}_j$, while the e_i picks out i^{th} row of the matrix of moving average coefficients, which is denoted by $\mathbf{B}_{i,\tau}$. If we assume that TFP measure is ordered first in this multivariate system, then the unanticipated shock will be indexed by 1. In addition, assume that a news shock is indexed by 2. As stated above, the identification relies on the assumption that all variations in TFP are driven by these two shocks, i.e. these two shocks account for all variations in TFP at all horizons, implying that:

$$\Omega_{1,1}(h) + \Omega_{1,2}(h) = 1 \;\forall\, h.$$

The contemporaneous shock is identified as the shock associated with the first column of the matrix $\mathbf{A}_0$. The news shock then corresponds to the innovation that explains all remaining variation in TFP conditional on being orthogonal to current innovations. The identification of the news shock amounts to choosing the impact matrix to maximize contributions to $\Omega_{1,2}(h)$ over h, or choosing the second column of the impact matrix to solve the following optimization problem:

$$\mathbf{D}_2^* = \text{argmax} \sum_{h=0}^{H} \Omega_{1,2}(h)$$

s.t.

$$\widetilde{\mathbf{A}_0}(1, j) = 0 \ \ \forall j > 1 \tag{A1}$$

$$\mathbf{D}_2(1, 1) = 0 \tag{A2}$$

$$\mathbf{D}_2'\mathbf{D}_2 = 1. \tag{A3}$$

Here, H represents an arbitrary truncation horizon. In the benchmark specification, following Barsky and Sims (2011) I set H equal to 40.

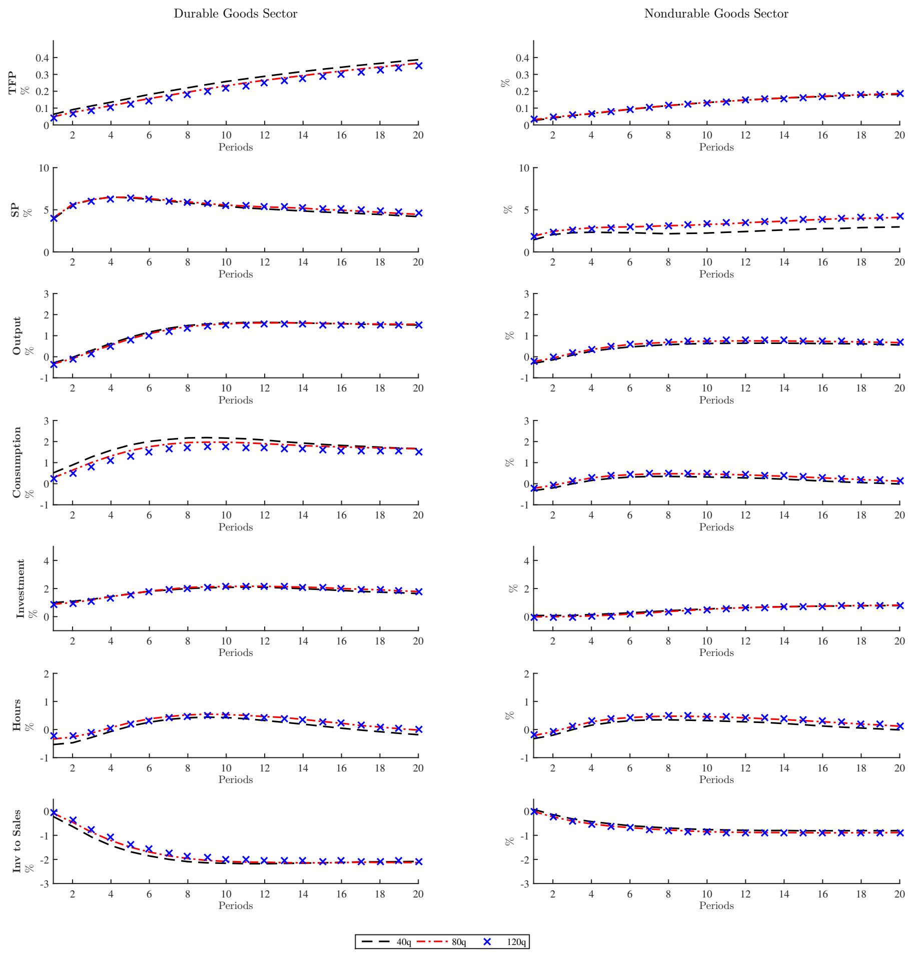
B Robustness of the Empirical Findings

In this part I perform two sets of robustness checks in regards to the identification scheme used. First, I check if results are affected by the use of different truncation horizons in the benchmark specification and, second, whether they are affected by the use of two different identification schemes: the one proposed by Francis et al. (2014) and the one proposed by Beaudry and Portier (2006).

B.1 Alternative Horizons in the Benchmark Specification

In this part, I perform robustness analysis by setting H equal to 80 and 120 when benchmark identification strategy is used. This robustness check is motivated by the finding of Beaudry et al. (2011) that their VAR responses are sensitive to the truncation horizon when using Barsky and Sims' method. Namely, they find that the impact response of hours, output and investment to news shocks is negative when 40-quarter truncation horizon is used, while, instead, it is positive when longer horizons, 80 and 120 quarters, are used. My results, however, are robust across all three different horizons when Barsky and Sims' method is used. This claim is supported by the responses displayed in Figure B1. In particular, the responses of all sectoral variables are very similar across the three different horizons, suggesting that the result presented in the main section of the paper are robustly estimated and do not depend on the forecast horizon used.

Figure B1: Sectoral Responses to News Shocks at Different Horizons



Note: The dashed, dash-dotted and crossed lines are the estimated impulse responses to a unit aggregate news shock (BS identification), when truncation horizon H is set to 40, 80 and 120, respectively. The unit of the vertical axis is the percentage deviation from the situation without a shock. The left hand panel represents responses of durable goods sector variables, and the right hand panel the responses of nondurable goods sector variables. The underlying VAR are exactly the same as the one used in the main text with the benchmark identification scheme.

B.2 Alternative Identification Schemes

B.2.1 Francis et al.'s Method

A quite similar identification strategy proposed by Francis et al. (2014) has been implemented by Beaudry et al. (2011), among others, to identify news shocks. Although quite similar to that of Barsky and Sims, this identification strategy assumes that although technology shocks should be the main drivers of productivity at long but finite horizons, other shocks can drive the evolution of productivity at these finite horizons as well. Because of this assumption, news shocks are identified by maximizing their contribution to the forecast variance decomposition of TFP at a finite horizon, h. In this case, therefore, the identification of the news shock amounts to choosing the impact matrix to maximize contributions to $\Omega_{1,2}(h)$ *at a fixed horizon* h, or choosing the second column of the impact matrix to solve the following optimization problem:

$$\mathbf{D}_2^* = \text{argmax } \Omega_{1,2}(h)$$

s.t.

$$\widetilde{\mathbf{A}_0}(1,2) = 0 \tag{B1}$$

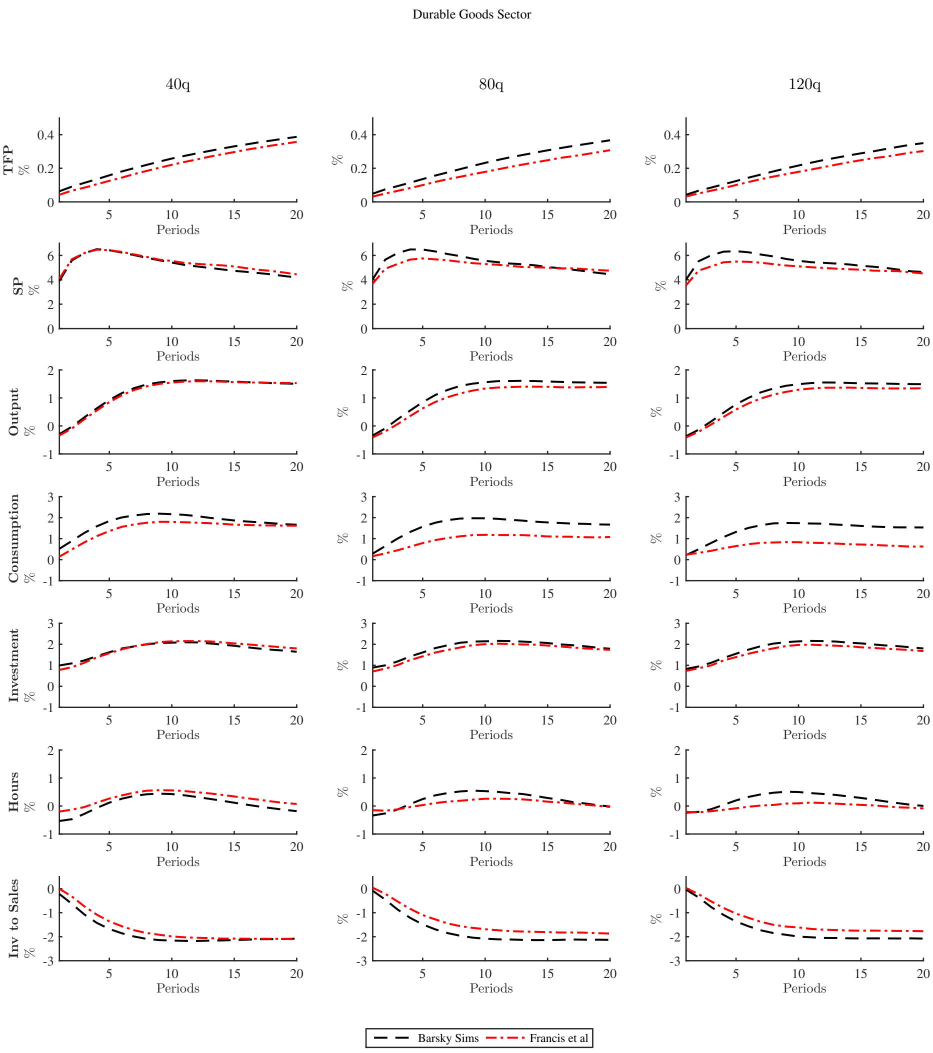
$$\mathbf{D}_2(1,1) = 0 \tag{B2}$$

$$\mathbf{D}_2'\mathbf{D}_2 = 1. \tag{B3}$$

As in the case of Beaudry et al. (2011), with Francis et al.'s method, my results are very similar regardless of the forecast horizon used. However, unlike these authors who find that the results are similar to those when Barsky and Sims' method is used only with longer horizons (80 and 120 quarters), I find that the results are very similar across the two identification schemes also when 40-quarter horizon is used. In sum, my results are robust across the two identification strategies over all horizons. This result is in line with Theodoridis and Zanetti (2016) who come to the same conclusion when investigating the responses of labor market aggregates to news shocks.

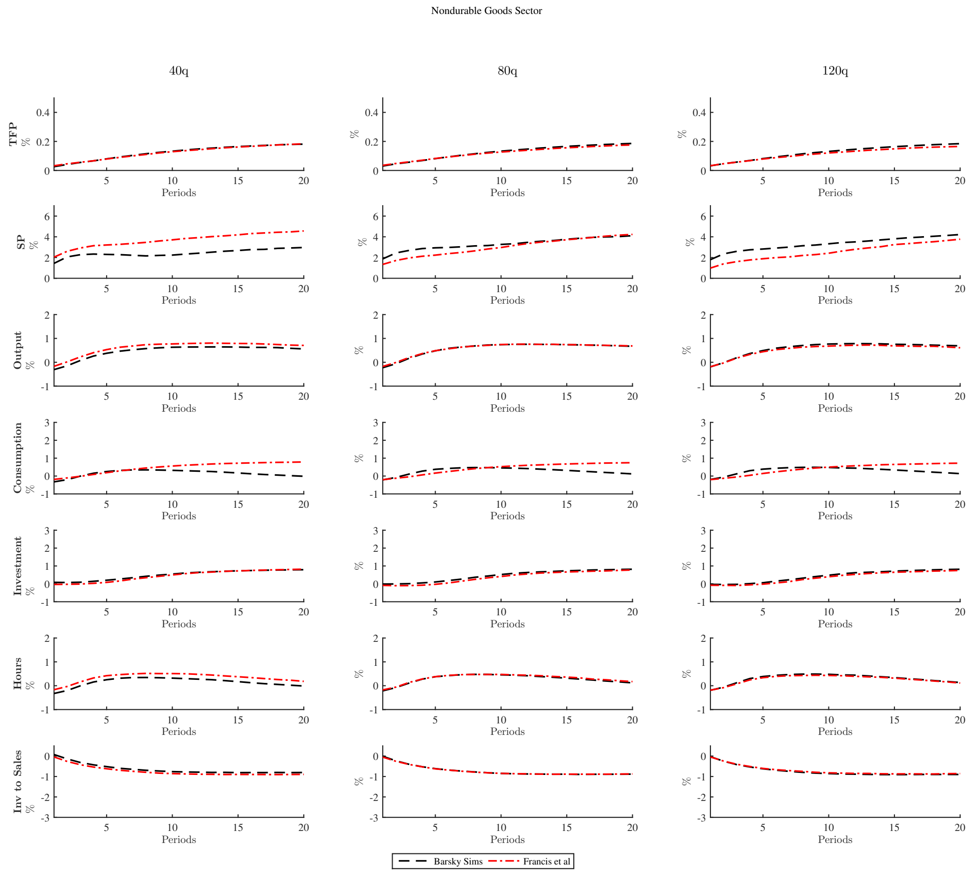
Figures B2 and B3 show the responses of fundamentals in the two sectors, respectively.

Figure B2: Responses of Durable Goods Sector Variables to News Shocks for Different Identification Schemes and Forecast Horizons



Note: The dashed and dash-dotted lines are the estimated impulse responses of durable goods sector variables to a unit aggregate news shock using Barsky and Sims and Francis et al.'s method, respectively. The left panel corresponds to h and H being equal to 40, middle panel to h and H being equal to 80, and the right panel to h and H being equal to 120.

Figure B3: Responses of Nondurable Goods Sector Variables to News Shocks for Different Identification Schemes and Forecast Horizons



Note: The dashed and dash-dotted lines are the estimated impulse responses of nondurable goods sector variables to a unit aggregate news shock using Barsky and Sims and Francis et al.'s method, respectively. The left panel corresponds to h and H being equal to 40, middle panel to h and H being equal to 80, and the right panel to h and H being equal to 120.

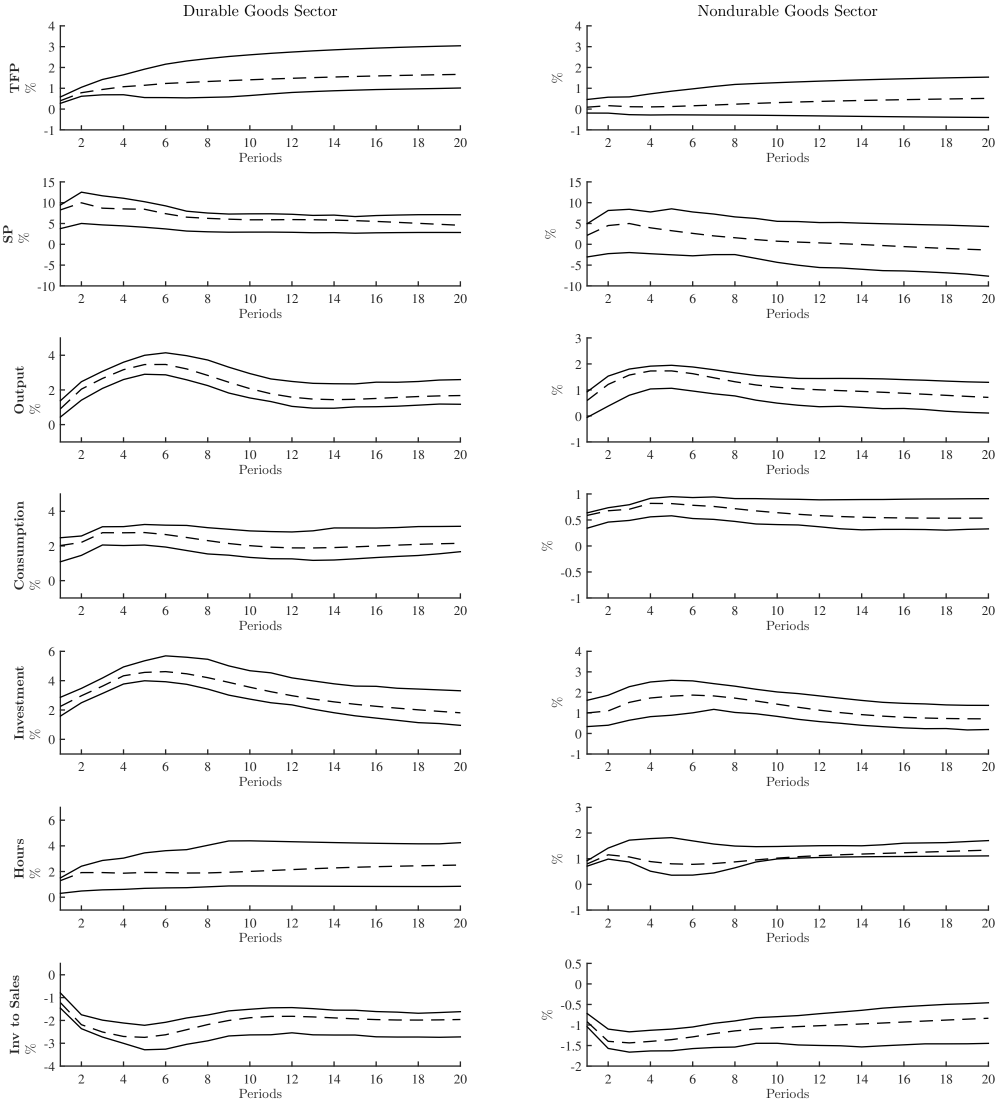
B.2.2 Beaudry and Portier's Method

Finally, an interested reader can learn whether main empirical results are robust to the use of Beaudry and Portier's identification method. This method relies on quite standard techniques of imposing short- and long-run restrictions with Cholesky decomposition. In particular, news shock is identified as a shock that does not affect productivity in the short run, but drives all of its variation in the long run. When I use this identification strategy, because of the issues discussed in the main body of the paper, I cannot use a large-scale VAR system. Therefore, I use the smallest possible VAR system (three-variable) that would still allow me to investigate effects of aggregate news shocks on sectoral fundamentals. The error bands are computed by bootstrapping from the estimated VAR. Figure B4 displays responses of the seven sectoral variables.

Contrary to my benchmark identification, this identification strategy implies comovement both within and across the two sectors. In fact, sectoral fundamentals react to a positive aggregate news shock in a positive way, reminiscent of the reaction of aggregate fundamentals after the same shock; fundamentals in both sectors comove. The impact responses of all fundamentals are larger than when the benchmark identification is used. It is also interesting that increase in output is not enough to satisfy both higher consumption and investment demand without a significant adjustment in inventories. This result suggests that, regardless of the identification scheme, inventories prove to be an important mechanism in channeling the response to news shocks.

Overall, these robustness checks suggest that that my second result, concerning the lack of comovement between fundamentals, is not robust to the use of Beaudry and Portier's identification. This is somewhat expected given the opposite implications of these two identification schemes when aggregate data is used. Nevertheless, more importantly, my first result concerning aggregate news shock being news about durable-goods-sector technological improvements and thus propagating through the durable goods sector, is robust to the use of these two different identification schemes. In addition, both identification schemes suggest an important adjustment of inventories in response to a favorable news shock.

Figure B4: Responses of Sectoral Fundamentals to a News Shock using Beaudry and Portier's Method



Note: Impulse responses of durable goods sector (left panel) and nondurable goods sector variables to a unit aggregate news shock, obtained using Beaudry and Portier's identification. The responses originate from a three-variable VAR featuring aggregate TFP, aggregate SP, and a sectoral variable which is alternatively TFP, SP, output, consumption, investment, hours, and inventories-to-sales ratio in each sector. All systems are estimated as a VECM with two cointegrating relationships, three lags and a constant. The dashed lines correspond to the OLS estimates of the VAR, while solid lines, obtained using the Monte-Carlo simulations with 1000 replications, correspond to the +/- one standard deviation confidence bands of the durable and the nondurable goods sector, respectively.